



HAL
open science

eSTIME: a visualization framework for assisting a multi-perspective analysis of daily mobility data

Aline Menin

► To cite this version:

Aline Menin. eSTIME: a visualization framework for assisting a multi-perspective analysis of daily mobility data. Computer Science [cs]. Grenoble UGA - Université Grenoble Alpes, 2020. English. NNT: . tel-03081054

HAL Id: tel-03081054

<https://hal.science/tel-03081054>

Submitted on 18 Dec 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

THÈSE

Pour obtenir le grade de

DOCTEUR DE L'UNIVERSITÉ GRENOBLE ALPES

Spécialité : **CIA - Ingénierie de la Cognition, de l'Interaction, de l'Apprentissage et de la Création**

Arrêté ministériel : 25 mai 2016

Présentée par

Aline MENIN

Thèse dirigée par **Paule-Annick DAVOINE**,
codirigée par **Luciana NEDEL**
et co-encadrée par **Sonia CHARDONNEL**

préparée au sein du **Laboratoire d'Informatique de Grenoble**
et de l'**Ecole Doctorale Ingénierie pour la Santé, la Cognition et l'Environnement (EDISCE)**

eSTIME: a visualization framework for assisting a multi-perspective analysis of daily mobility data

Thèse soutenue publiquement le **26 Novembre 2020**,
devant le jury composé de :

Monsieur Patrick Reignier

Professeur des Universités, Grenoble INP - ENSIMAG, Président

Monsieur Thomas Devogele

Professeur des Universités, Université de Tours, Rapporteur

Madame Sara Irina Fabrikant

Professeure des Universités, Université de Zurich, Rapporteur

Monsieur Christophe Hurter

Professeur des Universités, Ecole Nationale de l'Aviation Civile, Examinateur

Madame Julie Vallée

Directrice de Recherche CNRS, Laboratoire Géographie-Cités, Examinatrice

Monsieur Marco Winckler

Professeur des Universités, Université Côte d'Azur, Examinateur

Madame Paule-Annick Davoine

Professeure des Universités, Université Grenoble Alpes, Directrice de thèse

Madame Luciana Nedel

Professeure Agrégée, Université Fédérale du Rio Grande do Sul, Co-Directrice de thèse

Madame Sonia Chardonnel

Chargés de Recherche CNRS, Université Grenoble Alpes, Co-Encadrante de thèse



Once we accept our limits, we go beyond them.
Albert Einstein

Acknowledgments

The last four years have been an exciting and unforgettable experience, in both professional and personal aspects of my life. I had the opportunity of meeting incredible people, learning a new language, and I certainly know now a lot more about cheese and wine than I knew before! I would also like to believe that I have learned a thing or two about this great research field that is geography.

I would like to thank the members of the jury for the time dedicated to evaluating this work. Many thanks to the reporters Sara Irina Fabrikant and Thomas Devogele, whose reports added great value to the final version of this manuscript, and the examiners Christophe Hurter, Patrick Reignier, Julie Vallée, and Marco Winkler. I would also like to thank Thomas Devogele, Bruno Raffin, Thomas Thévenin, and Daniel Archambault for your research guidance as members of my monitoring committee.

A special thanks goes to my supervisors Paule-Annick Davoine, Sonia Chardonnel and Luciana Nedel for your support and research guidance over these four years, and thank you for your patience and support during my adjustment process to a new country, a new language, and a new research field.

On those lines, I would like to thank every member of the Steamer team and everyone I had the opportunity to meet in the corridors of the LIG, for making this experience easier and enjoyable. I would like to thank the permanent members of the Steamer team: Marlène Villenova-Olivier, Paule-Annick Davoine, Sonia Chardonnel, Danielle Ziebelin, Philippe Genoud, Sylvain Bouveret, Jérôme Gensel, and Carole Adam. I would like to thank my colleagues and former colleagues: Clément Chagnaud, Jacques Gautier, David Noël, Camille Bernard, Camille Cavalière, Lina Toro, Matthieu Viry, Matthew Streeves, Anna Mannai, Maeva Seffar, and Fatima Danash. Thanks to Michael Ortega for the collaboration in the development of the space-time cube. Finally, I would like to express my gratitude to Cécile Saint-Marc, Tales Paiva, Josiane Vale, and once again to Paule-Annick, whose hospitality, help and support were of the most importance upon my arrival in France to go through the administrative issues, the search of a place to live, and the first Christmas holidays away from home.

I would like to thank every volunteer that took part in the user experiments, which had a major importance in the development process of eSTIME. Particularly, I would like to thank Lucy Pichaud, Isabelle Reynaud, Arnaud SAILLET, Sandrine Astor, Magaye Sall, Sandrine Depeau, Isabelle André-Poyaud, Estelle Ployon, Sylvestre Duroudier, Kamila Tabaka, and Sarah Duche for allowing me to borrow your time and expertise to evaluate eSTIME.

I would also like to thank Marco Winckler and Fabien Gandon for the post-doc opportunity in the Wimmics team, where I hope to become a valuable member. I would like to extend my gratitude to my new colleagues, who are making of this opportunity a pleasant experience.

I would specially like to thank Marcely Zanon Boito, Francieli Zanon Boito, and Danilo Carastan for your friendship and all the coffee breaks that more than once helped me to get through a rough day or a rough bug!

I have no words to express how grateful I am to my family, my father Dilair, my mother Marilene, and my little sister Andreia, for everything they have done for me. Thank you for all your support and for believing in me. This day would not be possible without you!

Finally, I would like to thank Jens for all his help and support, and for everything that we have lived together since the day we met. I would also like to thank his family, Brigitte, Otto, Julia, Inge, Ruth, Elke, Markus, and the little ones, Fred and Carl, for welcoming me in their family as one of their own.

Abstract

The research field of urban mobility aims at the observation and design of human trips within an urban environment, which information supports decision-making and problem solving within public policies. In this context, there are many experts – not necessarily transportation specialists – that need to handle more or less standardized urban data to extract synthetic and easily exploitable knowledge. Hence, public transportation agencies commonly conduct trip-based surveys to collect information about day-to-day travel of the population within a particular territory (i.e. where and when we travel), resulting in large and complex datasets which analysis requires crossing spatial, temporal, thematic and socioeconomic dimensions to enable discoveries of daily urban mobility patterns. This way, information visualization is a suitable approach to support the analysis of urban mobility data, since analysts do not have to learn sophisticated methods to interpret the data visualizations that come to reinforce their cognition and enable the discovery of unstructured insights within the data. Thereby, we propose a visualization framework to assist the analysis of urban mobility through indicators describing complementary objects of interest within the data that allow to address three categories of questions underlying the urban mobility phenomenon. A first question seeks to understand the daily traveling routine of a population and the resulting processes of exchange between places, which can be studied through the exploration of amounts, modalities, direction, and variation of travel flows and trips according to different socioeconomic aspects of individuals and land types. A second questioning concerns the temporal variation of population presence throughout a territory, which allows to understand the use of distinct locations by taking into account the socioeconomic characteristics of the people visiting it and the activities they carry out there. The third question seeks to explain the individuals' need of traveling by studying the temporal ordering of trips and activities of individuals (i.e. daily trajectories) within the spatial context of the territory. Our framework supports the derivation and visual exploration of indicators describing the territory, travel flows and trips, and daily trajectories, over multiple spatio-temporal resolutions and thematic attributes. Our visualization interface allows to disperse visual representations over multiple analytical displays, enabling users to customize the spatial arrangement of visualizations and indicators in meaningful ways according to the ongoing analysis. Furthermore, we propose a movement-based interaction based on the tilting of a tablet that allows to explore the temporal variation of indicators leveraging tactile and tangible input. The conception of our visualization approach followed an interactive evaluation process that consists of successive user-based evaluations aiming to refine a prototype in order to achieve user performance and satisfaction.

Keywords: daily mobility, visualization, spatio-temporal data, activity patterns, visual analysis

Résumé

L'observation de la mobilité urbaine permet de produire des connaissances sur les pratiques de déplacements très utiles pour accompagner les prises de décision dans le cadre des politiques publiques urbaines. De nombreux experts - pas nécessairement spécialistes des transports - doivent traiter des données de mobilité urbaine plus ou moins standardisées pour en extraire des connaissances synthétiques et facilement exploitables. Les autorités organisatrices de la mobilité mènent régulièrement des enquêtes pour recueillir des informations sur les déplacements quotidiens de la population sur un territoire donné, dont les jeux de données qui en découlent sont nombreuses et complexes. Leurs exploitations requièrent des analyses qui croisent les dimensions spatiales, temporelles, thématiques et socio-économiques afin de découvrir les schémas ou profils spatio-temporels de mobilité quotidienne. Dans ce contexte, la visualisation des données est une approche appropriée pour accompagner ces analyses dans la mesure où elle renforce le processus cognitif de l'analyste pour découvrir des structures et processus dans les données sans être forcément expert des méthodes statistiques de traitements des données. Ainsi, nous proposons un environnement de géovisualisation pour aider à l'analyse de la mobilité urbaine à travers des indicateurs produisant des connaissances sur des objets d'intérêts complémentaires répondant à trois catégories de questionnements. Une première catégorie relève des connaissances liées aux déplacements quotidiens et aux processus d'échanges entre les lieux qu'ils génèrent. Des indicateurs sur le nombre, les modes, les motifs des déplacements, ainsi que les directions et intensité des flux entre les lieux sont explorés dans le temps et dans l'espace en fonction des attributs socio-économiques des individus. Une deuxième orientation de questionnements porte sur la variation temporelle de la présence de la population au sein des espaces d'un territoire tenant compte de sa mobilité. Des indicateurs permettent de visualiser les dynamiques de peuplement quotidien et de comprendre quels types de personnes fréquentent les différents "sous-espaces" et quelles activités elles y exercent au cours des 24 heures. Le troisième type de questionnements cherche à expliquer la mobilité des individus à travers leurs programmes d'activités. Il s'agit d'explorer l'ordonnancement spatial et temporel des déplacements et des activités des individus (aussi nommé "trajectoire quotidienne"). Nous proposons un environnement de géovisualisation qui permet l'exploration d'indicateurs décrivant le territoire, les flux et les déplacements et les trajectoires quotidiennes, à de multiples granularités spatio-temporelles et en fonction de divers attributs thématiques. Notre interface de visualisation permet de déployer les représentations visuelles sur plusieurs tableaux de bords analytiques ce qui donne aux utilisateurs la possibilité de personnaliser l'agencement spatial sur le ou les écrans des visualisations et des indicateurs en fonction des besoins de l'analyse en cours. De plus, nous proposons le déport des

fonctions de gestion et sélection des indicateurs et des attributs sur une tablette tactile et tangible. Le mode d'interaction est basé sur le mouvement corporel qui joue sur l'inclinaison de la tablette pour faire varier la dimension temporelle des indicateurs. Enfin, la conception de notre approche de visualisation a suivi un processus d'évaluation itératif basé sur des expérimentations successives menées auprès d'utilisateurs aux profils variés. Ce processus a permis d'affiner un prototype visant à améliorer la performance et la satisfaction de l'utilisateur.

Mots-clés: mobilités quotidiennes, visualisation, données spatio-temporelles, programmes d'activités, analyse visuelle

Contents

Publications	1
1 Introduction	17
1.1 Context and Motivation	17
1.2 Problem Statement and Research Questions	27
1.3 Contributions	32
1.4 Thesis Outline	33
2 State of the Art	35
2.1 Introduction	35
2.2 Visual Analysis of Urban Mobility Data	38
2.2.1 Travel Flows and Trips	40
2.2.2 Territory and Population Dynamics	49
2.2.3 Individual Trajectories	53
2.2.4 Multiple Objects of Interest	60
2.2.5 Synthesis	65
2.3 Non-conventional Displays and Interaction Techniques	71
2.3.1 Large, High Resolution Displays	71
2.3.2 Interaction via Handheld Devices	73
2.3.3 Multiple Displays	77
2.3.4 Synthesis	79
2.4 User-based Evaluation of Visualizations	80
2.5 Summary	84
3 The eSTIME Framework	85
3.1 Introduction	85
3.2 Data Preparation	87
3.2.1 Original Dataset	89
3.2.2 Information Matrices	94
3.3 Statistical Indicators and Typology	99
3.4 Querying	108
3.5 Interactive Visualization	114
3.5.1 Visual Encoding	116
3.5.2 TiltingMap	128
3.5.3 Interactive Exploration	132
3.5.4 History of User Activity	138
3.5.5 Technical Aspects	140

3.6	Use Case Scenarios	142
3.6.1	Scenario 1: The reasons driving human mobility	142
3.6.2	Scenario 2: The reasons and transportation means underlying traveling patterns	145
3.6.3	Scenario 3: The latent activity programs of daily mobility	147
3.7	Summary	150
4	User Evaluation	155
4.1	Introduction	155
4.2	Mutual Materials and Methods	157
4.3	Experiment I: eSTIME v1.0	165
4.3.1	Visual and Interaction Tools	166
4.3.2	Hypotheses	169
4.3.3	Materials and Methods	170
4.3.4	Results	175
4.3.5	Synthesis	179
4.4	Experiment II: TiltingMap	181
4.4.1	Hypotheses	181
4.4.2	Materials and Methods	182
4.4.3	Results	186
4.4.4	Synthesis	191
4.5	Experiment III: eSTIME v2.0	193
4.5.1	Visual and Interaction Tools	194
4.5.2	Hypotheses	197
4.5.3	Materials and Methods	198
4.5.4	Results	203
4.5.5	Synthesis	207
4.6	Experiment IV: Experts Feedback	209
4.6.1	Visual and Interaction Tools	210
4.6.2	Hypothesis	212
4.6.3	Materials and Methods	212
4.6.4	Results	217
4.6.5	Synthesis	220
4.7	Summary	222
5	Conclusion	227
5.1	Summary of Contributions	230
5.2	Future Research Perspectives	233
5.3	Final Considerations	242
	Bibliography	243

A	Typology of Activity Programs: Characteristics of Individuals	263
B	Territorial Partitions of Studied Regions	273
C	Mutual Materials and Methods of Experiments	277
D	Experiment I: Questionnaires and Tasks	283
E	Experiment II: Questionnaires	291
F	Experiment III: Questionnaires and Tasks	295
G	Experiment IV: Questionnaires	299

List of Publications

The following papers were published as part of this thesis:

- Menin, A., Chardonnel, S., Davoine, P.-A., Ortega, M., Dublé, E., and Nedel, L. (2020). eSTIME : une approche visuelle, interactive et modulable pour l'analyse multi-points de vue des mobilités quotidiennes. *Geomatica*, pages 1–22
- Tabaka, K., Duché, S., Menin, A., and Chardonnel, S. (2020). Metropolitan mobility and daily activities diversities and constraints: the Grenoble urban area case. In *CIST2020 - Population, temps, territoires*, Paris, France
- Menin, A., Chardonnel, S., Davoine, P.-A., Ortega, M., Duble, E., and Nedel, L. (2019b). eSTIME : une approche visuelle, interactive et modulable pour l'analyse multi-points de vue des mobilités quotidiennes. In *SAGEO Spatial Analysis and Geomatics*, Clermont-Ferrand, France
- Menin, A., Chardonnel, S., Davoine, P.-A., and Nedel, L. (2019a). eSTIME: Towards an All-in-One Geovisualization Environment for Daily Mobility Analysis. In *32nd SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*, pages 39–46, Rio de Janeiro, Brazil
- Menin, A., Chardonnel, S., Davoine, P.-A., and Nedel, L. (2018). Exploring Shifting Densities through a Movement-based Cartographic Interface (Short Paper). In *10th International Conference on Geographic Information Science (GIScience 2018)*, volume 114, pages 48:1–48:6, Melbourne, Australia

List of Figures

1.1.1	<i>Carte figurative de l'instruction populaire de la France</i> , 1826. Source: Dupin (1826)	22
1.1.2	Harness' Passenger Conveyance Map, 1837. Source: Robinson (1955)	23
1.1.3	Charles Minard's map of Napoleon's disastrous Russian campaign of 1812. Source: Minard (1869)	24
1.1.4	Temporal segmentation of a space-time path. Source: Shaw and Yu (2009)	25
1.4.1	The cyclic and incremental methodology underlying the conception of our visualization framework. Source: the author.	33
2.1.1	The design patterns of composite visualization views according to the spatial layout of component visualizations. Source: Javed and Elmqvist (2012)	37
2.2.1	The visual representation have the shape of a tangled and overlapping pile of links, which characterizes the graphic overcharge that causes the <i>spaghetti effect</i> . Source: http://www.martingrandjean.ch/wp-content/uploads/2016/05/airports-world-network.png	41
2.2.2	Flow magnitude from different directions and distance ranges are represented through radial diagrams which sectors represent directions from a particular location.	42
2.2.3	Geographical maps linked through heat maps to represent O/D flow data. The edge of each row/column is connected to an origin or destination map through lines, which flow magnitude is encoded by color.	43
2.2.4	The visualization of flow exchanges between bicycle stations via a chord diagram (top), and the effects of contextual attributes (e.g. weather, holidays) on hire amounts of a particular station through a parallel coordinated plot (bottom). Source: Shi et al. (2018)	44
2.2.5	Visual exploration of bus passengers flow. The arc diagram (a) represents flow exchanges between pairs of bus stations, and the pixel-based chart (b) displays flow magnitude per bus station and time interval, which color encodes magnitude from red (high) to green (low). Source: Wang (2016)	45

2.2.6	Visual exploration of mobility-related factors on a public transportation system. The <i>isochrome map view</i> (a) reveals the accessible regions from a particular location within a certain travel duration. The <i>isotime flow map</i> (b) visualizes mobility information along the time axis and clear pathways between O/D pairs. The <i>OD-pair journey view</i> (c) and the <i>mobility wheel</i> (d) display the temporal variation of waiting, transfer and riding times for a particular journey. Source: Zeng et al. (2014)	46
2.2.7	For a particular region selected on the map view (a), one can explore the incoming and outgoing flows dynamics over different days and time periods using the <i>OD-Wheel</i> (b). The detail view (c) displays the flow volume per travel distance along the day over a time granularity of 10 minutes. Source: Lu et al. (2016)	47
2.2.8	Visualization of latent activity patterns extracted from taxi, metro and telco data. Source: Wu et al. (2017)	48
2.2.9	Visual exploration of unusual phenomenon effects in passenger flow within a metro system. Source: Itoh et al. (2016)	49
2.2.10	The geographical maps (bottom) display the spatial distribution of different activity patterns; the circular views (top left) represent the distribution of people per age group; and the line chart (top right) represents the temporal evolution of patterns. Source: Yan et al. (2018)	50
2.2.11	Visual interface to explore the propagation of traffic congestion. The circles clears the locations where an incident occurred revealing the traffic conditions. The temporal variation of traffic can be explored via a timeline that gives the intensity of traffic incidents over time (bottom right). Source: Anwar et al. (2014)	51
2.2.12	The visualization of POI-mobility signatures. The charts are placed on regions of interest, which displays the mobility intensity over different time periods by means of a stacked graph, and the activity context via a pie chart. Source: Zeng et al. (2017)	52
2.2.13	Ranking based visual analysis of taxi travel behavior. Source: Lu et al. (2015)	53

2.2.14	The TrajectoryWall approach. The individual trajectories are represented as stacked 3D colored bands on a 2D geographical map (a). The <i>time lens</i> (b) displays travel attributes aggregated on time according to a spatial query. The <i>time graph</i> (c) displays trajectories as stacked horizontal bands. Source: Tominski et al. (2012).	54
2.2.15	The spatio-temporal representation of individual trajectories in the <i>RelationLines</i> visual approach. The radial charts depict weekly movement behaviors of individuals, which colors encode activities performed in the spatial position of charts on the map. Source: Chen et al. (2018).	55
2.2.16	Visual representation of an activity-time cube of six activity paths. From left to right: front, rotated and side view. Source: (Vrotsou et al., 2010).	57
2.2.17	The individual space-time paths are colored to encode different types of activities (a). A kernel density estimation algorithm reveal aggregate activity distributions surfaces at different time units (b). Space-time paths are clustered together based on their similar geometry (c). Source: Chen et al. (2011).	58
2.2.18	Typical space-time paths visualized through a sequence alignment method. The vertical pillars represent the stops of an individual, which height encodes the duration of the individual's trajectory and red segment encodes the time they spent there. Source: Shoval and Isaacson (2007).	59
2.2.19	Visualization of trajectory data using both the STC and a geographical map. Source: Gonçalves et al. (2016).	59
2.2.20	The iVizTrans interface. The spatial distribution of people according to their activities (home, work, others) at 10am (a). The spatio-temporal visualization of individual commuting trips (b). Travel flows from home to work locations (c). Source: Yu et al. (2015).	60
2.2.21	Spatio-temporal visualization of individual trajectories (a), hotspots of human activity (b), and flows of information or movement (c). Source: Gao (2015).	61
2.2.22	A visual analytics system for exploring sparse microblogging data. Source: Chen et al. (2015).	62
2.2.23	The Mobiliscope (Le Roux et al., 2017), a visual analytical system for studying social segregation. Source: Snapshot from https://mobiliscope.parisgeo.cnrs.fr/ .	63
2.2.24	The TelcoFlow visual interface. Source: Zheng et al. (2016).	63
2.2.25	The visual interface of TelCoVis. Source: Wu et al. (2015).	65

2.2.26	Distribution of surveyed papers according to types of analysis they support and thematic information they represent. Source: the author.	68
2.3.1	Multi-user CMV application on an interactive wall-sized display: (a) Interaction from close (touch) and distance (mobile device); (b) Data selection; (c) Details on demand; (d) Interactive ruler for value comparison; and (e) Magic lens with menu. Source: Langner et al. (2018).	73
2.3.2	Set of mobile-based interaction technique for LHRD-based graph visualizations. Source: Kister et al. (2017).	74
2.3.3	A mobile-based interaction technique to directly sketch visualization controllers. Source: Tsandilas et al. (2015).	75
2.3.4	A technique that enables 3D interaction with nearby large displays by vertically swiping a mobile device. Source: Pietroszek et al. (2015).	75
2.3.5	Bar chart visualization fixed on the mobile device (left) and in space (right). Source: Büschel et al. (2016).	76
2.3.6	Visualization approaches to increase screen space through the distribution of views throughout multiple screens and/or devices.	78
3.1.1	The eSTIME Framework supports the analysis of daily urban mobility on the basis of three complementary objects of interest explored through a four-step workflow. The (1) <i>data preparation</i> phase structures the input data and extracts information matrices, which are afterwards used for (2) deriving a <i>typology of activity sequences</i> and <i>statistical indicators</i> to describe daily urban mobility. The (3) <i>querying</i> stage establishes a system of queries to explore indicators over space, time, objects and attributes. Finally, the <i>interactive visualization</i> proposes visual and interaction tools to explore the data through our indicators and system of tasks.	87
3.2.1	The territorial partitions of the great region of Grenoble metropolitan area.	92
3.2.2	The data is organized into trips with depart and arrival times, trip purpose, transportation mode, and O/D locations (left), from which we derive the stops and moves (right). Adapted from: Cochey and Tabaka (2007).	96
3.2.3	Components and relationship among entities of human mobility data.	97
3.2.4	Information matrices of (a) flows, (b) presence, and (c) activity sequences. A flow matrix is calculated for each time unit.	98

3.3.1	Workflow of AGNES algorithm. At each step, leafs are clustered together based on their similarity. Adapted from: Kassambara (2020)	103
3.3.2	Dynamic Hamming Distance: an example. Source: Lesnard (2009)	104
3.3.3	The dendrograms resulting from the hierarchical clustering performed on the sets of daily trajectories of Grenoble, Lyon and Rennes metropolitan areas. The dashed line represents the height where we cut each tree to extract the clusters of the typologies.	106
3.4.1	Overview of the Triad (left) and Pyramid (right) frameworks. Adapted from: Peuquet (1994) , Mennis et al. (2000)	109
3.5.1	Overview of eSTIME visualization interface.	115
3.5.2	The maps represent indicators of business and fluctuation rates via the choropleth technique (top) and the presence of movers for business activity and fluctuation in different locations via the proportional symbols technique (bottom).	118
3.5.3	The <i>Mobility Wheels</i> representing the mobility rate indicator of <i>Oisans</i> , a suburban district in the region of Grenoble, along with attribute share (trip purposes (top) and transportation modes (bottom)). The donut charts display the attribute rate aggregate over 24 hours (bottom) or magnifies the indicator for a particular time interval (top). The gray rectangles encode time units when no movement was recorded.	119
3.5.4	The <i>flows diagram</i> is based on a chord diagram, which arcs represent nodes and ribbons connect related nodes (top left). The figure represents the estimated flows exchanges within Grenoble's inter-municipalities (12 districts) for business (top right). Upon selection, the connections of a particular location are highlighted and details on flow exchanges for that locations are displayed (bottom).	121
3.5.5	The <i>state distribution plot</i> . The <i>x</i> -axis represent time and the <i>y</i> -axis represents the indicator of either attribute or activity share.	123
3.5.6	The <i>sequences index plot</i> . The <i>x</i> -axis represents time from 4am (the day before) to 4am (the survey day) and <i>y</i> -axis the individuals. Color encodes activities (top) of stops and transportation modes of moves (bottom). Gray encodes the time period when the individual was traveling (top) or stationary (bottom). The details panel (left) displays information that describe the profile of individuals.	125

3.5.7	The representative trajectories of the typology’s fourth group. The 2D plane represents the territory of the urban area partitioned into small areas, while the height presents time as one-hour intervals. The color encodes activities of stops. The details panel (right) displays information that characterized the movers.	127
3.5.8	Functionality of the flip technique. When tilted vertically, different stripes of the map shift into the focus of the half-lenses. Source: Dickmann (2010)	129
3.5.9	The interactive styles of <i>TiltingMap</i> implemented on the basis of accelerator and gyroscopes inputs. Following the assumption that mobility patterns repeat themselves daily, we use a circular tilting movement to control time through a timewheel representation (top). We also provide a linear tilting movement to control time, due to the fewer degrees of freedom this movement requires compared to the circular one, and the familiarity of users to timelines (bottom).	131
3.5.10	The overall structure of eSTIME’s interactive visualization. A mobile device serves as a control unit for interacting with analytical dashboards through four interchangeable interfaces: the <i>data selector</i> for opening, closing and modifying indicators; the <i>spatio-temporal explorer</i> for querying indicators over different spatial locations and time units; the <i>trajectory explorer</i> for visualizing and exploring daily trajectories; and the <i>history panel</i> that records user activity.	133
3.5.11	The layout of each tab in the <i>tab-based menu</i> supports four windows, each one comprising a dropdown-based menu (A-I) for building and visualizing indicators, and a set of widgets (1-6) to interact with the current visualization on that window.	134
3.5.12	Overview of eSTIME’s activity flow.	137
3.5.13	The <i>history panel</i> of control unit <i>A</i> , which dashboard <i>B</i> is associated with. Each window has its own history, which records actions of opening/closing a view, attributes modification, environment restoring, global settings and interactive view switching. A menu is available over each episode (red dashed rectangle), allowing the user to restore the dashboard or entire environment to the time of that event, or to delete that event or all events from the corresponding window or dashboard from history.	139

3.5.14	The working flow of eSTIME. Firstly, the data goes through a cleaning and statistical treatment to calculate the mobility indicators. Secondly, the output data are visualized through Web-based technologies. The application can be instantiated multiple times simultaneously, with each setup comprising a control unit and at least one dashboard, which communication is managed by a central Websocket server. The control unit communicates yet with a second server, which provides and manages the space-time cube.	140
3.6.1	Scenario 1: Understanding the reasons that drive human mobility within the great region of Grenoble metropolitan area. .	144
3.6.2	Scenario 2: The reasons and transportation means underlying traveling patterns within the great region of Lyon metropolitan area.	146
3.6.3	Scenario 3: The travel-activity patterns resulting from daily trajectories of individuals within the urban areas of Grenoble and Lyon.	148
3.7.1	The four-step workflow followed to conceive the eSTIME visualization framework.	151
4.1.1	The eSTIME implementation cycle. Several user evaluations were performed to progressively improve our prototype. . . .	156
4.2.1	The general experimental protocol followed by every user-base evaluation.	158
4.2.2	The process of computing the mean workload score from the NASA-TLX questionnaire. Adapted from: Hart and Staveland (1988)	163
4.2.3	The workflow for performing the statistical analysis of the output data of the user studies.	164
4.3.1	eSTIME v1.0: (a) flows diagram and (b) mobility wheel. . . .	167
4.3.2	eSTIME v1.0: Control Unit interface. (a) A side navigation menu allows the opening/closing of indicators on the dashboards. (b) An automatic questionnaire guide the analytical tasks during the Trial phase and records the tasks' completion time. (c) The settings serve to change the time picker format: circular or linear (d), and to manage the questionnaire. The map (e) enables spatial filtering and the visualization of presence-related indicators.	168

4.3.3	The <i>TiltingMap</i> technique can be used through a circular or a linear time picker, which affects the tilting movement (rotational and left to right, respectively). The time representation can be changed at any time.	169
4.3.4	Environment setting of Experiment I. The tablet served as the Control Unit, the desktop monitor held the analytical dashboard, and the laptop served as support for typing the tasks' answers in a digital form.	174
4.3.5	Comparison of mean completion times per task (both sets combined) across experimental conditions.	175
4.3.6	Comparison of mean scores of NASA TLX workload-related factors across experimental conditions.	176
4.4.1	The protocol followed during the trial phase of Experiment II. The conditions 1-4 are replaced by a counterbalanced order of experimental conditions.	185
4.4.2	Mean completion times and response accuracy per task across experimental conditions.	187
4.4.3	Comparison of mean completion times per experimental condition between people that reported having recurrent pain or a medical condition involving their wrists/hands (blue) and people without pain in these body regions (red).	188
4.4.4	Participants rating of a statement reflecting the satisfaction of using each interaction style (top) and their choices of one style over the other in a pairwise comparison.	190
4.5.1	The menu interface was re-designed using the slideshow metaphor, which slides represent the dashboards and the four sections allow to directly choose where to visualize indicator, controlling the arrangement of visualizations on each dashboard.	194
4.5.2	The modifications made to the Mobility Wheel. (a) We used the <i>Jenks</i> natural breaks classification method to better represent the mobility rate values, which also reflects in more comprehensible color code and legend. (b) The bar charts were replaced by arcs, which leverage the same color code of the Mobility Wheel to represent transportation modes.	195
4.5.3	The modifications made to the Flows Diagram. A white gap has been drawn between arcs and ribbons to indicate incoming flows, and three peripheral bars present aggregate information about general, incoming and outgoing flows for each location.	196
4.5.4	The apparatus and setup of Experiment III. Twelve participants undertook the experiment simultaneously in a class-like environment.	202

4.5.5	Average response accuracy per indicator (right) and spatial location under analysis (left).	203
4.5.6	Mean completion times of tasks regarding each indicator. . .	205
4.5.7	Mean scores of RTLX for each workload-related factor and overall workload score.	206
4.6.1	The modifications applied to the Flow Diagram.	210
4.6.2	The modifications applied to the Mobility Wheel.	211
4.6.3	Protocol of the trial phase of Experiment IV.	214
4.6.4	The apparatus and setup of the Experiment IV. Two or four people side-by-side would explore the visual and interactive tools to complete the proposed tasks.	215
4.6.5	Participants ratings regarding the satisfaction statements in Experiment IV.	217
4.6.6	Mean scores of RTLX questionnaire per sub-scale and overall workload.	218

List of Tables

2.2.1	Surveyed publications according to the urban mobility issue they address.....	66
3.2.1	Summary of the datasets' sample for Grenoble, Lyon and Rennes metropolitan areas.	91
3.2.2	Number of locations per territorial partition within each dataset.	93
3.3.1	Summary of statistical indicators and the typology of activity patterns.	108
3.4.1	Tasks for exploring the variation of indicators over three dimensions of the data.	112
3.4.2	Tasks for exploring the variation of indicators over two dimensions of the data.	113
3.7.1	Summary of visual representations proposed for exploring the statistical indicators and the typology of activity patterns.	152
4.2.1	The Curved Grading Scale (CGS) proposed by Sauro and Lewis (2016) for assigning grades to usability as a function of SUS scores.	160
4.3.1	The sets of analytic tasks applied during the Experiment I.....	172
4.3.2	Combinations of experimental conditions and sets of tasks used in both parts of the Trial phase of Experiment I.	173
4.3.3	Summary of correlations found within workload-related factors and/or other variables.	177
4.4.1	The sets of analytic tasks applied during the Experiment II.	183
4.5.1	Set of tasks used during the trial phase of Experiment III.	201
4.6.1	Set of tasks used during the trial phase of the Experiment IV. .	216
4.7.1	Summary of user experiments outcomes.	223
A.1	Socio-demographic aspects of surveyed individuals in the urban area of Grenoble per group of the typology of activity programs.	264
A.2	Usage frequency of private transportation modes of the surveyed individuals of the urban area of Grenoble per group in the typology of activity programs.	265
A.3	Usage frequency of public transportation system (PTS) of the surveyed individuals of the urban area of Grenoble per group in the typology of activity programs.	266
A.4	Socio-demographic aspects of surveyed individuals in the urban area of Lyon per group of the typology of activity programs. . .	267

A.5	Usage frequency of private transportation modes of the surveyed individuals of the urban area of Lyon per group in the typology.	268
A.6	Frequency of walking and usage of public transportation system (PTS) of the surveyed individuals of the urban area of Lyon per group in the typology of activity programs.	269
A.7	Socio-demographic aspects of surveyed individuals in the urban area of Rennes per group of the typology of activity programs. .	270
A.8	Usage frequency of different transportation modes of the surveyed individuals of the urban area of Rennes per group in the typology of activity programs.	271

List of Acronyms

HCI	Human-Computer Interaction
STC	Space-Time Cube
HTS	Household Travel Survey
O/D	Origin-Destination
CMV	Coordinated & Multiple Views
CVV	Composite Visualization Views
PTS	Public Transportation System
VAS	Visual Analytics System
SUS	System Usability Scale
NASA-TLX	Nasa-Task Load Index
UMUX	Usability Metric for User Experience
CGS	Curved Grading Scale
DoF	Degrees of Freedom

Introduction

1.1 Context and Motivation

The knowledge resulting from the study of human movement patterns helps to understand transformation phases regarding the relationships between global and local development (Montanari, 2005), and to expand planning policies to provide transportation facilities to the users' demands (Horton and Wagner, 1969). The earliest studies about human mobility were primarily focused on the movement of a population within metropolitan areas due to the original forms of urbanization, which would concentrate places of production and residence in specific areas, making it easier to identify and predict commuting patterns. This suggests that individuals migrate based on their attraction by areas that offer better employment opportunities than those in their place of residence, which is no longer the case. Human mobility is also driven by recreation, tourism and new lifestyles which vary according to people's age and place of origin.

The political, technological and economic repercussions of globalization at the end of the 20th century changed the nature of human mobility, while reducing the differences between places of work, leisure, education and training (Montanari, 2005). Further, the *telecommuting* work arrangement, popular in the 21st century, eliminates the necessity of commuting to a central place of work (e.g., office building or warehouse). It allows teleworkers to use technologies such as Wi-Fi equipped laptops or tablet computers to work from coffee shops, or yet desktop computers and landline phones to do office work from home. In either scenarios, places of work, home and leisure (i.e. coffee shop) are ambiguous.

Particularly, within the research fields embedded by human mobility, we focus on *urban mobility*, which aims at the observation and design of human trips within an urban environment (Marilleau, 2005). During the last

30 years, researchers' attention have been placed on the analysis of individual urban travel behavior as an attempt to find ordering factors that can help urban and transportation planners to better understand and forecast the travel patterns in the city. Since the 1950s, conventional trip-based surveys have been used for assessing the relative performance of transportation alternatives. These surveys provide datasets that describe single trips through geographic (i.e. origin and destination locations, and possibly travel route), temporal (i.e. starting/ending time), and thematic information (e.g., trip purpose, transportation mode, and traveler information) (Yu and Shaw, 2004).

Although urban trip movements tend to be a closed-circuit system, in which people leave home, make one or more stops, and then return home (Horton and Wagner, 1969), individuals often participate in several daily activities at different time and locations, generating complex travel-activity patterns. The spatial distribution of trips, the travel purposes, linkages and distance could vary among different socioeconomic-occupational groups, which information could provide the basis for general modes of urban travel patterns (Horton and Wagner, 1969). In the early 1970s, the Swedish geographer Torsten Hägerstrand proposed the time-geography framework, in which space and time are basic dimensions of analysis. This promoted the evolution of conventional trip-based surveys into activity-based ones, which improved the quality of responses, but kept collecting a similar range of information. This transition allowed researchers to focus their attention on the travel-activity patterns underlying human travel behavior, which reflect the linkages between trips and activities, individual temporal constraints and dependencies of activity scheduling, and the underlying activity behavior that generates trips (McNally and Rindt, 2007).

In this work, we exploit data from household travel surveys (HTS) regularly carried out in France. Since 1976, more than 170 surveys have been carried out on all major French cities and involved about three quarters of the country's population (Richard and Rabaud, 2018). Depending on the territory size and type (i.e. urban or rural area), different surveys are available. The conventional HTS relates to urban areas and, further to the aforementioned information, gathers socio-demographic data to describe the interviewed person and household. These surveys are standardized throughout France, which enables to assess and compare public development and urban transport policies changes over time and across different territories.

Although individual and household travel behavior vary from day-to-day based on their trip purposes and constraints (Pas and Koppelman, 1987),

this behavior has been shown to be more stable during weekdays than weekends (Schlich and Axhausen, 2003). Thereby, the analysis of urban travel behavior is typically undertaken using data for a single day for each individual or household in the sample. Understanding the daily mobility patterns of individuals provide insights into their daily activities and livelihood, which can be used as a measure of life quality (Hägerstrand, 1970). Numerous professionals within urban policies, such as researchers, diagnostic managers, and local authorities use the outcomes of daily mobility analysis to assist decision-making on transportation offers, accessibility, air quality control, public health, well-being, crisis management, and others. In this thesis, we propose the study and categorization of the urban mobility phenomenon via the analysis of three complementary objects of interest within the data:

1. the description of *travel flows and trips* between spatial locations forms the skeleton of a urban or metropolitan spatial system. The flow patterns and spatial structures are the outcome of long-term development and their basic character is reproduced and confirmed by everyday human activity, which can themselves be responsible for reshaping the mobility patterns. For instance, the construction of a shopping center in a suburban location could significantly reshape the pattern of travel for shopping in the metropolitan area (Novák and Šykora, 2007).
2. the dynamics of a *territory* described through the variation on presence and absence of people over time reveal the spatiotemporal activity of an urban area across multiple temporal resolutions, i.e. the urban pulse of a city (Miranda et al., 2016). This information helps to understand where and when people agglomerate, which could help the government to anticipate the consequences of natural disasters or epidemics, and to propose investments that are consistent with the real rhythm of the city.
3. the *daily trajectories*, defined as the daily activity programs of individuals, i.e. the sequences of activities and trips one performs over a 24-hour period of time. Their analysis together with social and economic information can help to better understand the mobility needs and constraints of different population groups (Chen et al., 2011).

Individual aspects (e.g., social class and position, ethnicity, life cycle status, and residential location) are determinant factors of activity and travel patterns, which are themselves impacted by social roles and norms, resource constraints, and perception of opportunities (Fried et al., 1977). A single socio-demographic variable is unlikely enough to define population sub-groups for

modeling all aspects of travel behavior (Hanson and Hanson, 1981). Some well-known urban mobility patterns show that:

- the overall travel frequency does not depend only on trip purpose but also on automobile availability (Hanson and Hanson, 1981);
- travel decisions are made within the context of household demands, which directly relate the household size to individuals' travel frequency (Hanson and Hanson, 1981), and trips distance (Pouyanne et al., 2005);
- people with higher social status travel longer distances to perform their activities, and their trips would also have a higher number of stops, indicating that they are mostly multipurpose in nature, as opposite to the trips performed by individuals of lower social status (Hanson and Hanson, 1981, Horton and Wagner, 1969).
- women tend to perform numerous and shorter trips than men, being mostly restricted to their residential zone (Horton and Wagner, 1969, Hanson and Hanson, 1981, Pouyanne et al., 2005);
- younger individuals, men, married people, and those without a full-time job engage more frequently in out-of-home social activities (Hanson and Hanson, 1981); and
- the urban form influence travel patterns (Pouyanne et al., 2005) in a way that
 - high density settlements enable shorter trips, which reduces the use of automobile, while increasing the use of soft transportation modes, such as bicycles;
 - residential areas mainly composed of isolated houses encourage the ownership and use of automobiles, and therefore, promote longer trips originating from these places.

The phenomenon of urban mobility is often described through large and complex datasets, which analysis requires crossing spatial, temporal, thematic and socioeconomic dimensions to reveal those well-known patterns and/or to enable new discoveries within the data. These outcomes will which serve to support decision-making and problem solving within public policies to provide outputs of a political system, such as transportation policies, management of public health service and education systems.

The accelerated population growth required the data collection process to reach a greater number of people in order to accurately assess the performance of current public policies and to propose suitable ones according the socio-economic and demographic profiles of different populations. Furthermore, the technological growth made it easier and faster to collect greater amounts of data describing people's movements within a particular territory. Therefore, there are nowadays numerous, complex and huge datasets that require powerful and user-friendly software, for supporting the extraction of synthetic knowledge to describe the urban mobility phenomenon. Moreover, movement data is intrinsically spatio-temporal, which implies on considering the variation of urban traveling patterns over space and time.

Information visualization proposes visual representations of abstract data to reinforce human cognition, which allows the discovery of unstructured insights limited by human imagination and creativity. In this context, analysts do not have to learn sophisticated methods to interpret the data visualizations, which makes it suitable to support the analysis of complex and large datasets. Although powered by technological solutions, the use of visualization is not a new practice. Visual imagery has been an effective way to communicate both abstract and concrete ideas since the dawn of humanity, which examples include the cave paintings and Egyptian hieroglyphs.

A Brief History of Cartography and Time-Geography

The graphical representation of a geographical area, i.e. *cartography*, date from the prehistoric depiction of hunting and fishing territories, which discipline became popular in the 14th century when the earliest world maps were compiled for navigation ([Encyclopædia Britannica, 2017](#)). Cartography provides tools that allow to model reality in ways that effectively communicate spatial information by combining science, aesthetics, and technique. Particularly, the branch of *thematic* cartography supports the communication of more than geographical locations and relationship, including themes, patterns, and data relating to physical, social, economic, political and other aspects of a geographical location. Hereafter we briefly describe the origin of thematic cartography and the time-geography, which concepts enable a visual representation of urban mobility data through the analysis of the three aforementioned objects of interest.

Thematic and flows cartography

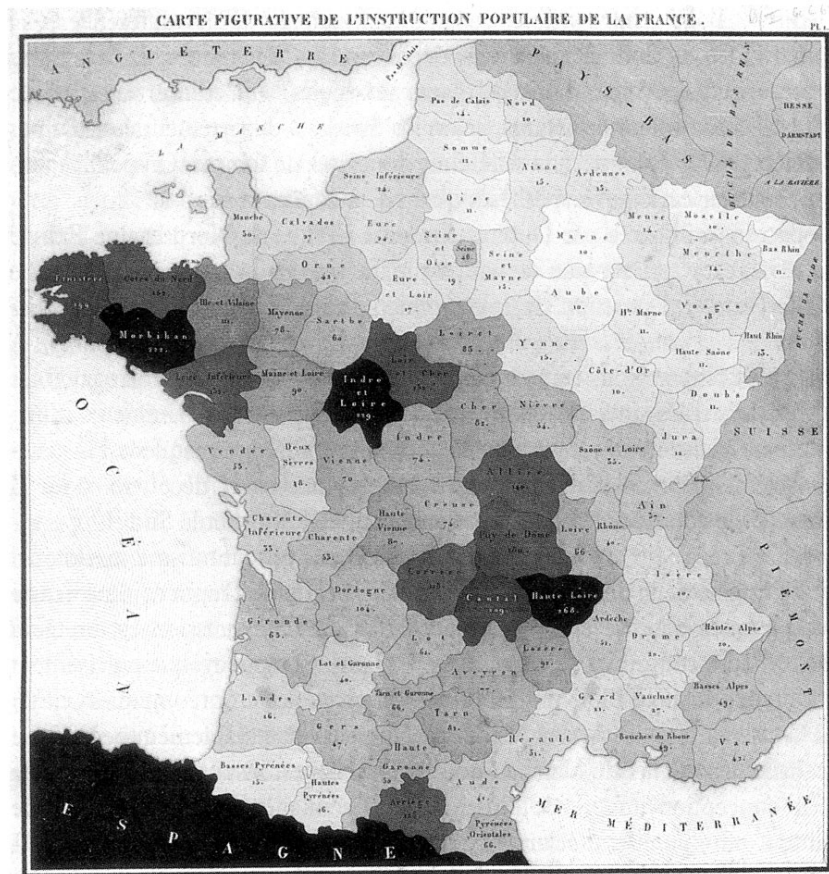


Figure 1.1.1: *Carte figurative de l'instruction populaire de la France*, 1826.
Source: Dupin (1826).

Thematic maps (i.e. maps showing the connection between themes and specific geographic areas) emerged in the 19th century, when events such as the industrial revolution, the launching of great topographic surveys, the instauration of censuses, and the proliferation of investigation and education of physical and social science provided an opportune environment to the development of geographical cartography (Robinson, 1955). The first choropleth map was conceived in 1826 by Charles Dupin to illustrate the theme of primary education by *département* in France (Palsky, 2008). The “*Carte figurative de l'instruction populaire de la France*” was conceived to verify the connection between people’s education and prosperity (Dupin, 1827), and uses color intensity to encode education level (Figure 1.1.1). In fact, almost every technique known for representing population numbers, distribution, density and

movements were introduced during a short period of 20 years between 1835 and 1855 (Robinson, 1955).

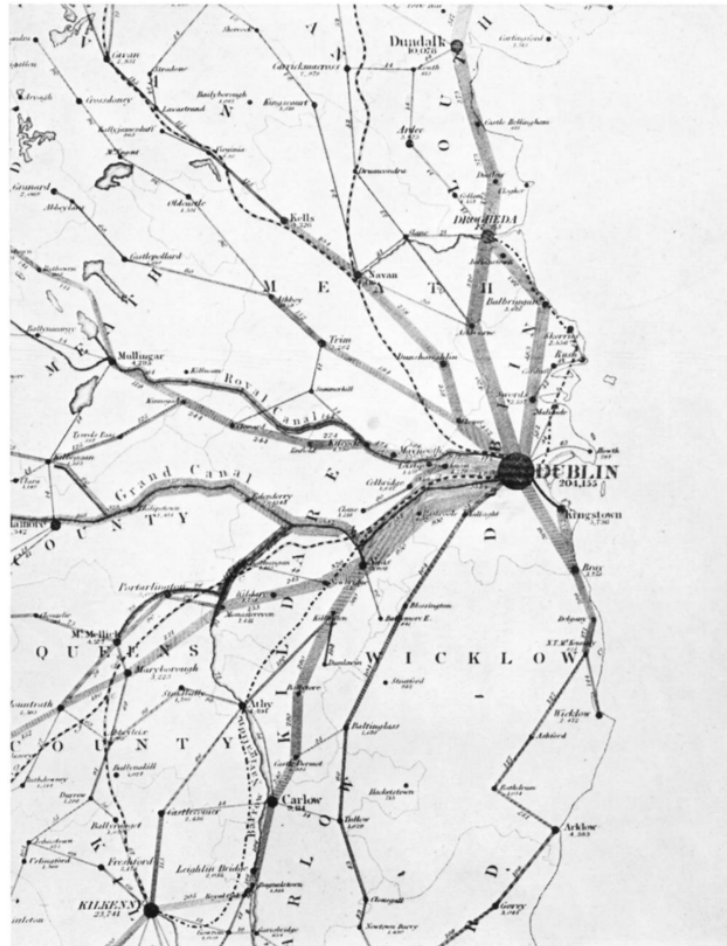


Figure 1.1.2: Harness' Passenger Conveyance Map, 1837. Source: Robinson (1955).

Around 1837, the cartography of flows emerged in England through a set of maps designed by the British soldier Henry Drury Harness to accompany the Second Report of the Irish Railway Commissioners, which examples include the Passenger Conveyance map (Figure 1.1.2). The map displays the routes of regular public transportation through ribbons, which thickness represents the number of passengers traveling in different directions (Robinson, 1955). Nevertheless, flows cartography became known only around 1869 through the famous map of Napoleon's disastrous Russian campaign of 1812 (Figure 1.1.3), conceived by the French engineer Charles Minard. The map depicts Napoleon's army campaign in Russia through a band graph (i.e. Sankey diagram), which band thickness encodes the size of his army at specific geo-

graphic points during their advance and retreat. The chart displays six types of data in two dimensions: number of troops, traveled distance, temperature, latitude and longitude, traveling direction, and spatial location at different dates.

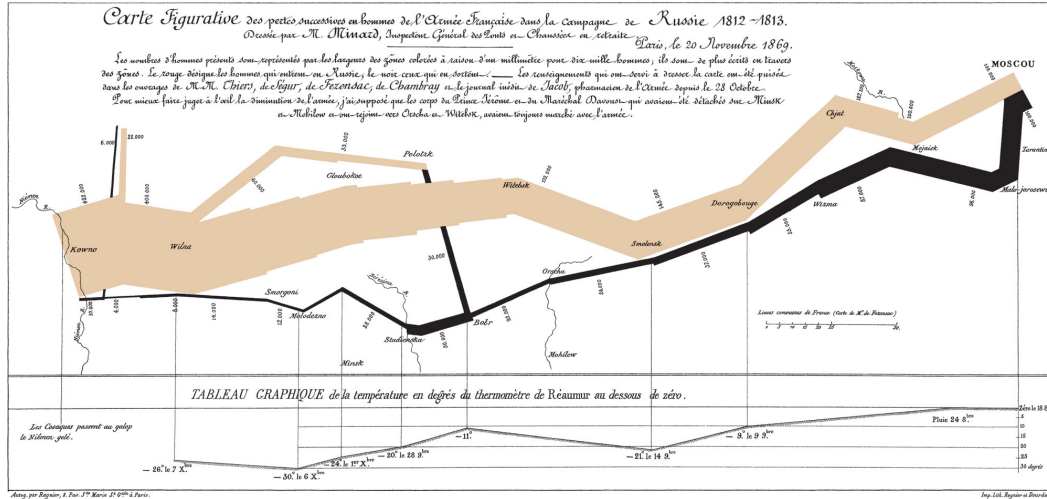


Figure 1.1.3: Charles Minard’s map of Napoleon’s disastrous Russian campaign of 1812. Source: [Minard \(1869\)](#).

These examples show the suitability of maps to visualize a spatial situation due to their capacity of summarizing the complexity of reality via an abstract representation of data ([Kraak, 2006](#)). Nevertheless, movement data is intrinsically spatio-temporal, which introduces the necessity to investigate the variation of a spatial situation over time. This exploration is often supported by time-juxtaposing and animation techniques. The former, also known as *small multiples*, enables the representation of time-series data by displaying several maps side-by-side, which leverage our common exposure to sequential art and the absence of occlusion, simplifying their interpretation ([Bach et al., 2017](#)).

Animated maps have long drawn the interest of cartographers to display the interrelations among space, attributes and time components ([Kraak et al., 1997](#)), since we live in an animated world and humans possess an eye-brain system that is finely tuned to seeing (perceptually) and understanding (cognitively) motion and change. The concept of animation became popular in the 1950s, when Norman Thrower animated a series of static maps through photographic tricks ([Thrower, 1959](#)). Twenty years later, the American-Swiss geographer and cartographer Waldo Tobler created one of the first animations as it is known today, using a 3D map generated through computer graphics

to portray population growth in the city of Detroit over a specific time period (Tobler, 1970).

Time-geography

In order to represent life stories of people and their interaction in space and time, Hägerstrand (1970) introduced the idea of a space-time cube (STC), which consists of a 2D geographical space (depicted on the cube's basis) plus time (depicted via the cube's height). Together with symbols and colors, one can easily represent movement data through space, time and thematic information. The STC is a suitable approach to display and analyze paths of (multiple) individuals, groups or other objects moving through space and time, since it supports the perceptual integration of multiple data dimensions (Kraak, 2003).

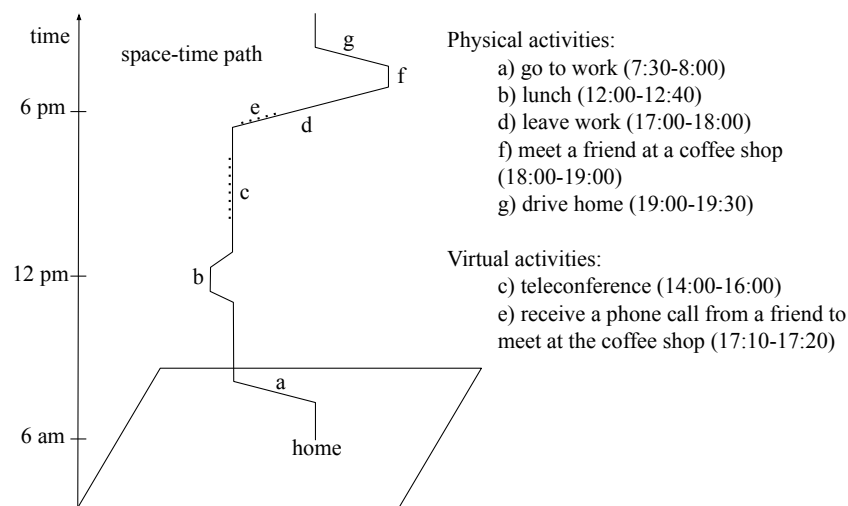


Figure 1.1.4: Temporal segmentation of a space-time path. Source: Shaw and Yu (2009).

The pioneer implementation of the STC in a geographical information system (GIS) belongs to Kwan (2000). The author used activity travel diary data organized in the form of a space-time path (Figure 1.1.4) and activities were represented as projects, i.e. sequences of actions undertaken in the pursuit of predetermined goals (Adams, 1995). Everything being done (including “to do nothing”) is considered an activity, thus every point in the space-time path is associated to at least one activity, which may occur in the virtual (e.g. e-shopping and online education) or physical space, causing multiple tasks

to overlap each other, such as a mobile phone call while traveling from one location to another (Shaw and Yu, 2009).

The technological development allows to continuously innovate the way we use visualization to communicate information, while fulfilling the demands of new generations. This way, these disciplines, i.e. information visualization and cartography, together became a new field of research known as *geovisualization* (short for geographic visualization), which enables the design and development of powerful tools for visual analysis and communication of information.

Although the term visualization has been known in cartography since the early 1950s, *geovisualization* developed as a field of research only in the early 1980s, based largely on the work of the French cartographer and graphic theorist Jacques Bertin, known for his book *Semiology of Graphics* (Bertin et al., 1967). Since then, geographers and computer scientists work together to develop conceptual frameworks and methodologies to provide visual and exploratory analysis of spatio-temporal data, which includes human movement data (Andrienko et al., 2016b).

Nowadays, various combinations of these conventional and novel interactive visualization techniques are found in the literature to support the analysis of human mobility data at different spatio-temporal granularity levels and thematic attributes. However, they are often conceived to answer specific questions, such as traffic jam detection (Anwar et al., 2014), usage patterns of shared bicycle systems (Yan et al., 2018), and life trajectories analysis (Otten et al., 2015), which results on a partial description of the human mobility phenomenon. Further, the majority of these mobility patterns are explored through purely spatio-temporal data, which lacks the semantic information that support the understanding of complex travel behavior by considering activity chains and modes of transport that characterize people's movements (Noulas et al., 2012) (see Chapter 2 for a complete review of the literature), and only a few visualization systems provide the analysis of human mobility at the individual level.

The design of a visualization environment that provide the analysis of urban mobility at both population and individual level, while covering space, time and thematic information at different granularity levels requires:

- to design and develop appropriate visualization and interaction techniques to represent the mobility indicators while handling the dialogue

between space and time, and the data exploration at different levels of aggregation; and

- to consider the reasoning mechanisms supporting the visual analysis and the cognitive process associated, which results in different ways to which users perceive the visual representations.

In the following, we present our research problematic and questions while delineating the main challenges we attempt to overcome throughout this thesis.

1.2 Problem Statement and Research Questions

A better understanding of the daily mobility practices is a relevant issue when defining local public policies that favor sustainable and plural mobility practices within urban areas, which help to ensure the good health of the population by promoting air quality and the use of active modes (i.e. pedestrian and bike traffic) (Offner, 2020). Thus, more than just calibrating the transportation infrastructure via the understanding of travel flows, it is necessary to understand how individuals' activity programs influence their needs for mobility and service (e.g., shopping, leisure) and how these programs impact the usage of different places within a metropolitan area. In this context, many experts within public policies need to manipulate more or less standardized mobility data – without being transport specialists – in order to extract synthetic and easily exploitable knowledge. Particularly, we intend to provide solutions of visual analysis for the following three categories of users:

- the professionals of mobility (e.g., researchers, technical developers), whose goal would be to enrich the already acquired knowledge about human mobility patterns and their temporal variations;
- the professionals within public policies (e.g., urban planners), whose objective would be to integrate the mobility data in a global analysis of urban and territorial dynamics to propose solutions for transportation policies, accessibility, public health, well-being and others; and
- the experimental users, whose goal would be to report on a cohort study of individual mobility by easily exploring their datasets.

In this spirit, the main goal of this thesis was to conceive a visualization framework that facilitate the exploration and analysis of daily urban mobility data via three categories of questions of great concern within the fields of geography and urban planning, defined as follows:

1. *How the inhabitants of a territory move around on a daily basis? What are the resulting processes of exchange between geographical areas within the territory?* Hereafter, the *trips* correspond to the object of interest, which we address the amounts (per individual and population), modalities (purposes and transportation modes), and variation according to different socioeconomic aspects of individuals or land types. Afterwards, we describe the spatial structure resulting from daily mobility by deriving *travel flows*, which are the aggregate of trips between places of origin and destination (O/D).
2. *What is the temporal variation of population presence throughout a territory?* This question allows to better understand how the different locations are used by taking into account the socioeconomic characteristics of the people that visits it and the types of activities they carry out there. These spatial locations are the object of interest, which we analyze to estimate the presence of people at different times of the day. Thus, one must specify the boundaries of locations and time step at which to observe the variations in presence. These analyses provide better knowledge regarding the daily rhythms of the studied territories.
3. *What are the latent activity patterns of mobility?* This question seeks to understand how the individuals order their activities and trips over time in the spatial context of the territory. We focus on the *daily trajectories*, which are defined as a space-time path described by activities performed in each visited place and transportation modes used to travel from one place to another. The temporal sequences of activities extracted from the space-time paths are used to set up typologies to describe the diversity of daily activity programs underlying the traveling demands (Robette, 2011).

The framework should include the whole process of preparing the input data to derive the mobility indicators that allow to respond the above mentioned questions. Furthermore, it should support the visualization of these indicators through appropriate visual representations and interaction mechanisms to enable the exploration of data over multiple spatio-temporal granularity levels and thematic attributes. Ideally, the approach should allow the

effortless integration of new datasets (i.e. automatically prepare, derive and visualize indicators) for enabling the comparison of daily urban mobility patterns within different urban areas. On a more particular level, the approach should enable users to

- describe the daily mobility from the perspectives of travel flows and trips, the territory, and daily trajectories, which are themselves characterized by demographic, socioeconomic and travel-related aspects;
- explore and compare indicators at the aggregate **and** individual levels through suitable visual and interaction tools within a single environment to leverage their complementary aspect;
- explore the temporal variation of indicators to reveal the dynamics resulting from the human mobility phenomenon; and
- compose the visualization display in meaningful ways according to the ongoing analysis. Although the complementary aspect of indicators is essential for understanding the human mobility phenomenon as a whole, each aforementioned question could focus on indicators derived from only one object of interest, which could be also interesting for the analyst. Therefore, assuming users may not need to deal with every indicator and their spatio-temporal combinations simultaneously, we should allow them to display, hide, and modify visualizations according to different indicators, spatial locations, time intervals and thematic attributes as it better fit their analysis.

The multivariate aspect of movement data implies on manifold indicators defined over space, time, objects and thematic attributes, which analysis over different levels of aggregation and granularity (i.e. the level of detail in the dataset) could rapidly become complex. As mentioned earlier, information visualization is a suitable approach to assist the analysis of urban mobility data since it reinforces human cognition through visual representations of abstract data. However, the range of visualization techniques becomes larger and more diversified every day, which requires the designer of a such visualization framework to carefully select the appropriate visual representations and interaction mechanisms that enable data querying without increasing cognitive attention. Thus, the proposed visualization interface should be validate through user-based evaluations to ensure usability and user satisfaction. During the course of this thesis, we attempted to answer a set of research questions organized

over three fields of research: visualization, interaction and user-based evaluations. We defined them as follows:

1. *How to **visualize** indicators describing the territory, travel flows and trips, and daily trajectories over multiple granularity levels of space and time while taking into account the thematic information?*

As we have seen earlier, maps are essential and successful to represent the spatial dimension of mobility data, enabling particularly the analysis of territory dynamics and travel flows. However, depending on the underlying visual encoding that represents thematic information, maps can present cognitive and graphical limitations, which hinder the understanding and extraction of information (Bahoken, 2016b, Fish et al., 2011). Further, the time-geography approach was a breakthrough for spatio-temporal data, and particularly, space-time paths representation, while including thematic information. The first implementations of the STC appeared around twenty years ago, thirty years after it was conceptually introduced. However, the technology revealed some formerly unnoticed shortcomings of the concept such as information loss and occlusion caused by exploring a 3D visualization on a 2D display through basic interaction techniques unsuited to leverage the full potential of a 3D virtual environment (Bach et al., 2017). The use of 3D interaction technologies (e.g., virtual reality) appears to be the more suitable approach to reduce the negative effects of these deficiencies (Filho et al., 2020). Nevertheless, the democratization of 3D technologies might take some time. The challenge relies on meeting our requirements by designing new visualization techniques; improving the existing ones to reduce their negative effects on user performance; or combining available techniques to leverage the positive aspects of each one.

2. *How to leverage **interaction** for establishing the relationship of indicators with space, time and thematic dimensions while handling data exploration at different levels of aggregation and granularity?*

Analytical displays¹ are powerful decision-support tools able to transfer, at a glance, the relevant information to the analyst by presenting charts as tiled displays, with each display visualizing a different perspective to the data (Few and Edge, 2007), while increasing spatial thinking

¹The dictionary, Merriam-Webster's Collegiate Dictionary (1828), defines *display* as "an electronic device (such as a LCD) or part of a device (such as the screen of a tablet) that presents information in visual form", which is the definition we use throughout this thesis report.

and user performance (Fischer, 2018). However, screen space is a limited resource, which reduces the amount of screen space that can be allocated to each view and, consequently, the number and diversity of indicators that can be explored simultaneously. Likewise, it restricts the approach of juxtaposing time slices for representing the variation of data over time by reducing the resolution of every additional image. Further, the animation relies strongly on human memory, which makes it sometimes difficult to understand or follow the successive changes. Therefore, our challenge relies on comfortably and efficiently accommodate the necessary visualizations to explore the different perspectives of urban mobility data, while overcoming the cognitive and technological drawbacks of these well-known techniques to enable spatio-temporal exploration of indicators without increasing cognitive load.

3. *How to **evaluate** the visualization approach to ensure usability and user satisfaction?*

The process of designing a visualization framework that fulfill the aforementioned requirements could increase the cognitive load due to the integration of several visualizations to represent different indicators exploitable at various spatial, temporal and thematic granularity levels. Therefore, user evaluations should be conducted to ensure that the proposed approach does not increase cognitive attention in a way that negatively affects user experience and, consequently, the analysis outcomes. A review of the literature performed by Ellis and Dix (2006) showed that only a small number of authors evaluate their visualization proposals with participation of users, which may be consequence, among other things, of a difficulty to (1) recruit a group of “real users” (i.e. people working on the domain for which the visualization tool was conceived), and (2) replicate, in an experiment, the exploratory tasks for which visualizations are suitable. Furthermore, the authors conclude that any evaluation would be insufficient on telling whether a visualization works or not, but that empirical evaluations together with reasoned justification would lead to a reliable validation of the visualization. Despite the difficulty to completely assess a visualization, gathering feedback from users, specially experts on the domain, is extremely relevant to improve the visual and interactive tools, while ensuring usability through minimal cognitive attention and a pleasant user experience. Therefore, our challenge relies on finding a solution to appropriately evaluate the usability and suitability of our visualization framework to explore urban mobility data.

1.3 Contributions

The main contribution of this thesis comprises the design and implementation of a visualization framework that enable the analysis of daily urban mobility through the exploration of three complementary objects of interest: territory, travel flows and trips, and daily trajectories. On a more particular level, the framework embeds two contributions within the fields of interaction and information visualization.

Firstly, in order to overcome the well-known limitations of time animation we propose *TiltingMap*, a movement-based interaction technique designed to ensure better control of time animation and improve time reading. The technique implements the lenticular printing metaphor, allowing the user to view a different version of the indicator according to the tilting angle of a tablet, which is mapped to one of the twenty-four time periods on a time picker representing a whole day. The inspiration of this design comes from the possibility of leveraging users' proprioceptive sense, which is triggered by physical interaction and has shown benefits for improving memory, enjoyment and spatial navigation (Arvola and Holm, 2014, Besançon et al., 2017, Maciel et al., 2010). In our context, the proprioception is activated on users' hands and wrists via the tilting movement of a tablet.

Secondly, we designed and implemented eSTIME², a multi-display visualization system that embeds customizable analytical displays, which the user can personalize in meaningful ways according to the ongoing analysis. We provide a set of six visualization techniques, which the user can customize according to indicators, spatio-temporal granularity levels and thematic attributes that suits their analysis, and to disperse the visual representations over the multiple analytical displays, which each one supports the simultaneous exploration of up to four tiled and synchronized maps and charts. In an attempt to facilitate interaction with multiple screens, we leverage the tablet tactile input to control visualizations (i.e. open, close, modify indicators) in each analytical display, and the tablet's screen to visualize certain indicators. The system leverage a large visualization space, which can be progressively increased via the addition of another display, allowing the simultaneous exploration and comparison of multifaceted data through various indicators and over multiple spatio-temporal granularity levels and thematic attributes. Further, we offer the possibility of exploring time through animation and juxta-

²The visualization interface is accessible at <http://lig-coin.imag.fr/estime/>

posing techniques, which latter also allows the comparison of indicators over other data dimensions, such as space and semantic.

1.4 Thesis Outline

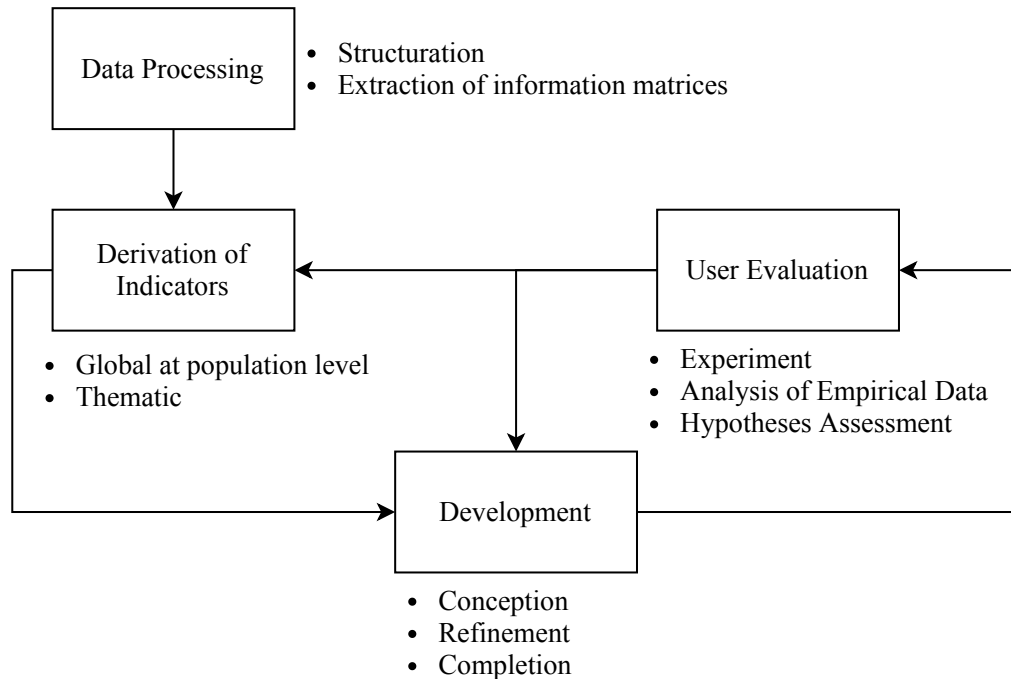


Figure 1.4.1: The cyclic and incremental methodology underlying the conception of our visualization framework. Source: the author.

During this thesis, we followed a cyclic and incremental methodology consisting of four phases (Figure 1.4.1). Firstly, we study the data we are dealing with and process it for extracting information matrices. Secondly, we use these matrices for deriving indicators from our three objects of interest. Thirdly, we implement a first prototype including indicators that enable the study of the urban mobility phenomenon through indicators describing the territory, travel flows and trips. The interface implements the multi-display approach and the interaction mechanisms that enable data querying. Afterwards, the prototype undergo a user-based evaluation process that aims to identify usability issues, which outcomes are used to refine the visual and interaction tools. The process continues as the refined prototype undergo subsequent usability evaluations, and we derive the remaining indicators to complete the prototype. Ultimately, we present eSTIME to a group of experts that help us to validate

the suitability of our visualization framework to answer the domain-related questions, specifically the three questionings that drove this research.

In order to ease the reading of this document, instead of presenting these steps in the chronological order that they happened, we present them in the order of a single passage through the process, which results in the arrangement described hereafter.

Chapter 2 describes the state-of-the-art of urban mobility visualization. Firstly, we present an extensive (yet not exhaustive) literature review of visualization techniques and visual analytical systems designed to support the exploration of urban mobility data through indicators of travel flows and trips, population and territory dynamics, and daily trajectories. Secondly, we present relevant solutions to overcome the screen space shortcoming when using multiple linked views. Finally, we present a literature review regarding user-based evaluations methods, their advantages and limitations whilst applied to the evaluation of visualization interfaces.

The Chapter 3 presents our contributions to the fields of visualization and interaction. Firstly, section 3.2 described the process of data structuring and derivation of indicators. Section 3.4 presents a system of tasks for guiding the user queries over space, time and thematic dimensions through our visual and interactive tools. In Section 3.5 we present the reasoning that led to *eSTIME*, the used visual encoding and interaction techniques, including the reasoning and development of *TiltingMap*. Finally, section 3.6 describes a set of usage scenarios to demonstrate the use of our visual and interactive tools to explore real data sets.

The user-based evaluations are presented in Chapter 4. Section 4.3 describes the first experiment, which was designed for gathering feedback on the first prototype of *eSTIME*. Section 4.4 presents an user experiment that evaluates the usability of *TiltingMap* with regard to the traditional animation technique. Section 4.5 present an user experiment performed to evaluate the usability of an improved prototype of *eSTIME*. Finally, the experiment presented in Section 4.6 involved experts on mobility and transportation to evaluate the suitability of our visualization framework for solving domain-related tasks.

In chapter 5 we present our final considerations regarding the contributions done in this thesis, the lessons we learned during the realization of this work, and discuss the possibilities of future research derived from this work.

State of the Art

2.1 Introduction

Numerous professionals within urban policies with possibly no knowledge in transportation, statistics or visualization, such as researchers, diagnostic managers, and local authorities, use the outcomes of daily urban mobility analyses to assist decision-making on public policies such as transportation offers, accessibility, public health, well-being, and air quality control. As a remainder, we propose the analysis of daily urban mobility data via the derivation of indicators describing three complementary objects of interest (i.e. flows and trips, population and territory, and daily trajectories) over space, time, and thematic attributes.

The multi-dimensional aspect of the data requires a diversified range of visualizations to better summarize and transfer the information. Further to representing the information over multiple spatio-temporal granularity levels, the definition of space goes beyond two or three coordinates, including the geographical context, which is difficult to formalize and represent. Moreover, time modeling can be linear and cyclical, often comprising several temporal cycles simultaneously (monthly, weekly, daily, etc) (Andrienko and Andrienko, 2007). The use of composite or multiple visualizations supports the representation of high complex, large scale, or heterogeneous data (Javed and Elmqvist, 2012), which make them essential to provide enough flexibility and power to deal with the complex analyses resulting from the combination of ordinary data dimensions (e.g., thematic attributes) with space and time (Andrienko and Andrienko, 2007).

The use of multiple views can increase user performance by supporting the discovery of unforeseen relationships and unify the desktop (North and Shneiderman, 1997), while reducing the cognitive load produced by a single and complex view of the data. However, the poor design of multiple view

systems could decrease their utility, both in terms of higher cognitive overhead (e.g., increasing the load on working memory, the time and effort required to learn the system, and to make comparison tasks and context switching) and increased system requirements (e.g., requiring high computational and display space resources). Therefore, [Baldonado et al. \(2000\)](#) propose a set of guidelines that establish the use of multiple views in situations where:

- the data contains at least one type of *diversity* regarding attributes, models, user profiles, levels of abstraction, or genres;
- the additional views are *complementary*, bringing out correlations or disparities within the data;
- the *decomposition* of complex visualizations into smaller and manageable views could reduce the amount of data held in the visual working memory; and
- there is a compelling reason to introduce additional views (i.e. the use of *parsimony*)

The remaining guidelines establish the means to present and interact with views: whether to display them sequentially or side-by-side to *optimize resources of space and time*; to make relationships within the data *self-evident* via perceptual cues; to be *consistent* throughout interfaces and states; and to ensure the *user's attention* is at the right place at the right time.

The term *multiple views* designates the representation of data in several windows. The typical layout of a multiple view system place visualizations in subsequent windows and the operations on each view are coordinated, the so-called *Coordinated and Multiple Views (CMV)* ([Roberts, 2007](#)). A standard implementation of CMVs comprises several statistical graphics and/or geographical maps embedded into analytical displays to represent individual entities and/or aggregates (e.g., histograms) linked together by brushing and selection techniques ([Andrienko and Andrienko, 2007](#)). [Javed and Elmqvist \(2012\)](#) introduced the notion of composite visualization views (CVV) as a theoretical model intended to unify the CMV paradigm with other strategies for combining visual representations in the same geometrical space. The authors derive design patterns according to the spatial layout of component visualizations defined as follows:

- the *juxtaposed views* (Figure 2.1.1a), which place visualizations side-by-side in one view (e.g., CMV), leveraging the independence of components that can be composed without interference. However, the technique suffer from the implicit visual linking among views that is sometimes difficult to perceive, and the shared space between views, which yields less space for each view;
- the *integrated views* (Figure 2.1.1b), which place visualizations in the same view with visual links, making it easier to perceive one-to-one and one-to-many relations between items. The drawback lies on the additional visual clutter to the overall view, and the shared display space between views. Further, the components have dependencies to enable visual linking;
- the *superimposed views* (Figure 2.1.1c), which overlay two visualizations in a single view, leveraging direct comparison in the same visual space. Nevertheless, it may cause occlusion and high visual clutter, since both visualizations share the same spatial mapping;
- the *overloaded views* (Figure 2.1.1d), which use the space of one visualization for another, leveraging more flexibility and control over visual clutter, even though the latter is increased. Further, the components are highly dependent on each other; and
- the *nested views* (Figure 2.1.1e), which nest the contents of one visualization inside another, leveraging a compact representation. However, each visualization has limited space and the visual cluttering and dependencies between components are high.

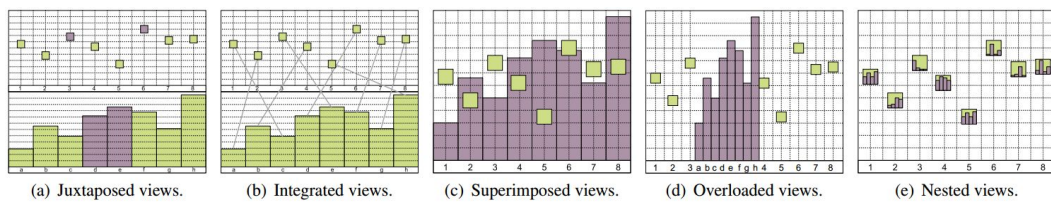


Figure 2.1.1: The design patterns of composite visualization views according to the spatial layout of component visualizations. Source: [Javed and Elmqvist \(2012\)](#).

These visualization methods combined with human-computer interaction mechanisms and the cognitive capabilities of human beings allows to extract knowledge from otherwise meaningless data ([Raghavan et al., 2016](#)). This process is known as *visual analytics*, which is the science of analytical reasoning

supported by interactive visual interfaces (Keim et al., 2009). Hence, visual analytics systems (VAS) embedding multiple views are widely used to represent multivariate data and support decision-making in diverse areas. Particularly, this chapter focuses on identifying the visual and interactive techniques supporting the analytical reasoning within VASs designed for urban mobility analysis.

The remaining of this chapter is organized as follows. Section 2.2 presents an extensive (yet not exhaustive) literature review of VAS classified according to the objects of interest addressed by the analysis. Section 2.3 focus on the use of analytical displays and their use together with large, high resolution displays and innovative interactive techniques leveraging kinesthetic interaction. Section 2.4 present the urban-based evaluation methods usually employed for evaluating the usability and suitability of visualization interfaces, and discuss the advantages and difficulties to implement it. Finally, Section 2.5 summarizes the visual, interactive and evaluative aspects of these previous works and discuss to what extent they could respond to the problematic addressed in this thesis.

2.2 Visual Analysis of Urban Mobility Data

Although surveys (e.g., travel, activity, and household-travel surveys) remain a great source of information to assess the performance of transportation systems within metropolitan areas, the emergence of tracking technologies promote the surge of new data sources to describe human movements, which themselves open up research opportunities within visual analytics. The visualization techniques and systems presented in this section enable the analyst to explore and extract urban mobility patterns described from data of diverse sources. Therefore, to guide the reader through the remaining of this chapter, we delineate the main types of data used in previous works, as follows:

- the *call detailed records (CDR)* are geo-referenced records produced by a telephone exchange that document the details (without the content) of a telephone call. They are typically used by telecom operators to troubleshooting and improve the network's performance. Nevertheless, each data record (i.e. a telephone call) contains information describing its starting/ending date and time; the identifier of who made it and who was called; its duration; whether it was incoming or outgoing; and the

originating/terminating towers (Sammons, 2015), which coupled with external data on customers (e.g. age or gender) makes CDRs a rich and informative source of data to study personal mobility, geographical partitioning, urban planning, and so on (Blondel et al., 2015);

- the *telco data* are exchange records between each mobile phone and cell stations when users make phone calls, send messages or connect to internet. This type of data has significantly increased with the popularity of smartphones running various apps both in the back and foreground, opening up opportunities for in-depth study of human behaviors (Zheng et al., 2016);
- the *taxi trip data* include information of pick-up and drop-off dates/-times and locations, trip distances, itemized fares, rate and payment types, and driver-reported passenger counts. Taxis are considered a valuable sensor to assess many aspects of urban life, such as economic activity and human mobility behavior (Ferreira et al., 2013);
- the *check-in data* is provided by applications such as Foursquare and Twitter, which allow one to announce their arrival at a hotel, airport, hospital and so on. Further to information on the type, name, geographical location and attendance time of a visited place, the data is often semantically enriched with users impressions on the place or event linked to that location;
- the *bike-sharing data* originate from bicycle-sharing systems, which dispense bicycles to individuals on a short term basis for a price or fee. These systems embed smart-technology that were at first intended to overcome losses from theft, and enable nowadays the collection of information on when and where bikes were borrowed/returned, and on the individual who rented it (e.g., their age). This type of data has a great potential on revealing human mobility behavior. However, bicycles are often used to travel short distances, which means the data would likely describe only the mobility patterns of people traveling within a part of the city, often downtown; and
- the *smart card data* contain records from validation cards used in subways and buses that provide information on where and when a passenger touched in/out. This type of data can be very useful to transport planners, from the day-to-day operation of the transportation system to the strategic long-term planning of the network (Pelletier et al., 2009).

These data sources describe movements through purely spatio-temporal information. Therefore, to semantically enrich the data, each data record is often segmented into moves and stops, which are coupled with external data to estimate information such as activities and transportation modes (Paiva Nogueira, 2017). The stops' positions in space help to estimate places of interest (POIs), which function could suggest the activity one performed while staying in that place (e.g. a restaurant would suggest the stop was for lunch or dinner according to the time it took place), and/or certain socio-demographic aspects of people, such as their occupation based on the time spent in a business-like place. Transportation modes are sometimes explored by combining different data sources, such as taxi trajectory, public transportation and bike-sharing data, which could help to distinguish the movements performed by car, bus, train, metro and bicycle, for instance. Another approach would be to combine the information on start/end time and trip duration with external data (e.g. train, flights timetables) to determine which transportation mode was used to perform each trip (Chen et al., 2015).

The remaining of this section is organized as follows. Subsection 2.2.1 presents visual techniques and VAS that enable ones to explore travel flows and trips. Subsection 2.2.2 focus on the visual analysis of presence dynamics over time of a population within an urban area. Subsection 2.2.3 focus on the visualization of trajectories on space, time or both. Subsection 2.2.4 presents visualization interfaces that allow the simultaneous and complementary analysis of two or three of these objects of interest.

2.2.1 Travel Flows and Trips

The analysis of human movement flows reveals the degree of connectivity and accessibility of a territory. For instance, within a metropolitan area, this information helps to understand how the urban core is connected to the less-populated surrounding territories. The description of flow variation over time helps to describe the appealing aspect of different locations according to when people move the most towards or from certain regions or locations. Further, information on trip purposes and transportation modes help to understand how the urban environment enables the establishment of these inter-territorial connections at different times of the day, which is relevant to make pertinent investment decisions on public transportation and activities such as the construction of new leisure and shopping places.

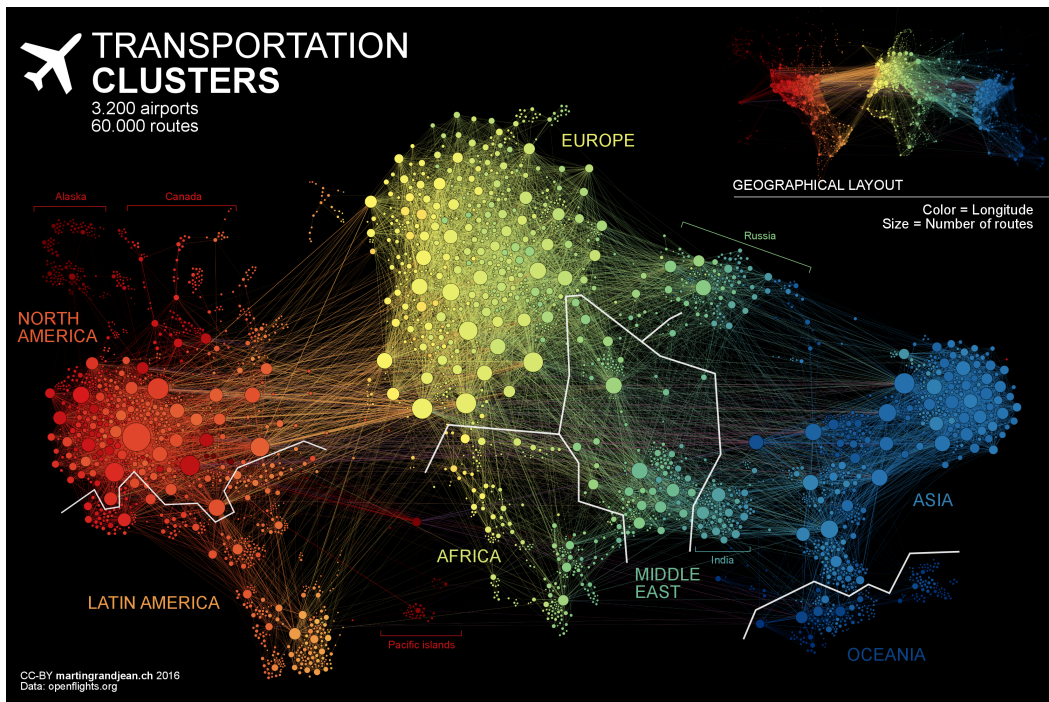
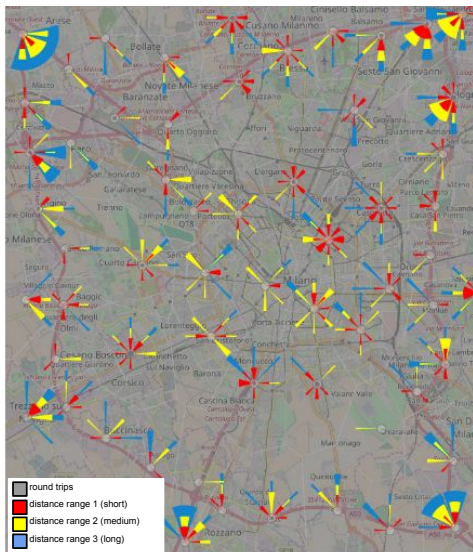


Figure 2.2.1: The visual representation have the shape of a tangled and overlapping pile of links, which characterizes the graphic overcharge that causes the *spaghetti effect*. Source: <http://www.martingrandjean.ch/wp-content/uploads/2016/05/airports-world-network.png>.

Flow maps are a combination of maps and flows charts that enable the depiction of movement flow between origin and destination (O/D) spatial locations. These O/D locations are represented by their geographical positions and therefore unchangeable, which often causes the arrows and lines to overlay each other provoking the well-known *spaghetti effect* (Bahoken, 2016b) (see Figure 2.2.1). However, the understanding of flow data is strongly dependent on the geographical information to provide visual insights on aspects such as distance, neighboring area, and surface of the involved territories. Therefore, we begin by summarizing previous contributions attempting to improve travel flow representation via the enhancement of flow maps' symbolism (Koylu and Guo, 2017); the abstract representation of space embedded into common charts; or the use of CMVs approaches, which link geographical maps and abstract flow charts through interaction techniques.

In order to reduce data dimensionality and improve interactive analysis, rather than intersecting lines, Andrienko et al. (2016a) and Jiang et al. (2015) visualize aggregate O/D data by drawing radial diagrams at the places of trip

origins or destinations, which can represent the count of trips to/from different directions and distance ranges. Color encodes the latter in Figure 2.2.2a, while several inner rings (i.e. tracks) encodes distance on the diagram of Figure 2.2.2b, where each track represents a certain distance range from the represented location, and orientation is encoded by sectors (e.g., a circular partitioning into 10°). The superposition of tracks and sectors results into pixels, which color encodes the number of trips having the given location as destination.



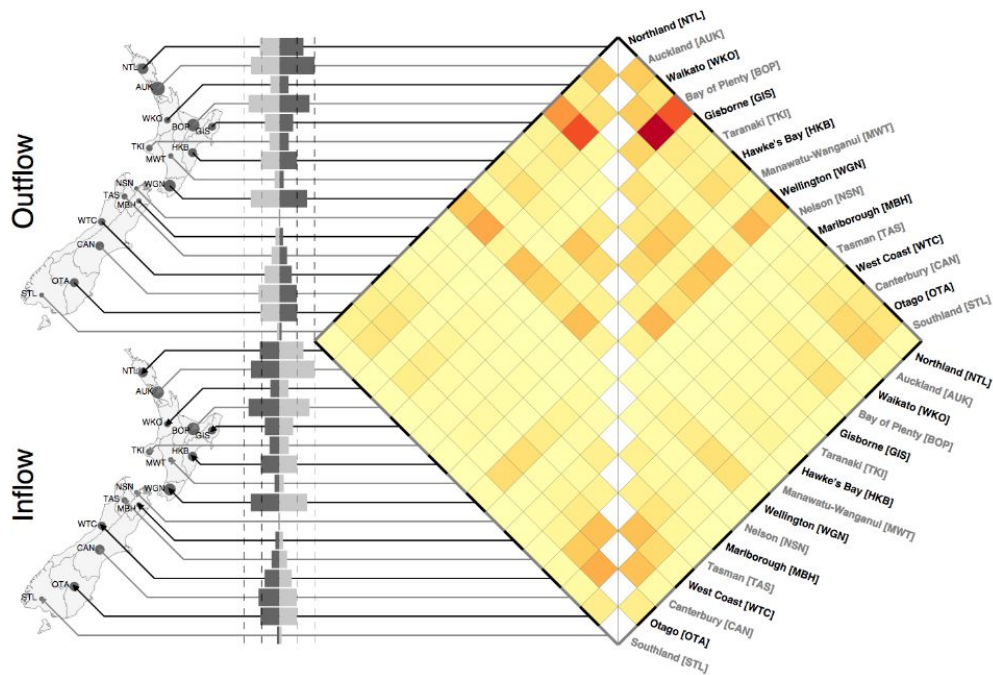
(a) Source: [Andrienko et al. \(2016a\)](#).



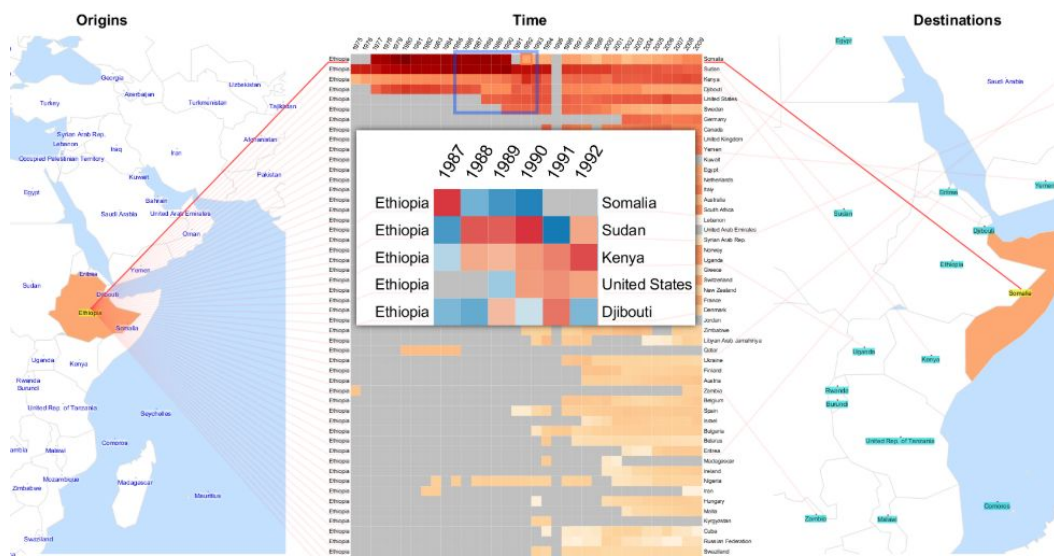
(b) Source: [Jiang et al. \(2015\)](#).

Figure 2.2.2: Flow magnitude from different directions and distance ranges are represented through radial diagrams which sectors represent directions from a particular location.

The intersection of rows and columns within an O/D matrix display the number of trips between O/D locations, which implies that these types of matrices could be easily transformed into heat maps, where cells are colored to encode the flow magnitude between each O/D pair. However, this visualization technique cannot represent geographical information, which led [Yang et al. \(2016\)](#) and [Boyandin et al. \(2011\)](#) to propose techniques that link two geographical maps through an O/D matrix (Figure 2.2.3). In this visualization, lines connect the edge of each row/column to their geographical position in both origin and destination maps. In addition, the Flowstrates technique (Figure 2.2.3b) reveals the temporal variation of flow magnitude by converting the matrix's columns into time intervals and the rows into pairs of locations. The authors propose yet a variation of the flow matrix that uses color hue



(a) MapTrix. Source: Yang et al. (2016).



(b) Flowstrates. Source: Boyandin et al. (2011).

Figure 2.2.3: Geographical maps linked through heat maps to represent O/D flow data. The edge of each row/column is connected to an origin or destination map through lines, which flow magnitude is encoded by color.

(red, gray, and blue) to encode the difference of flow magnitude between a time period to the previous one.

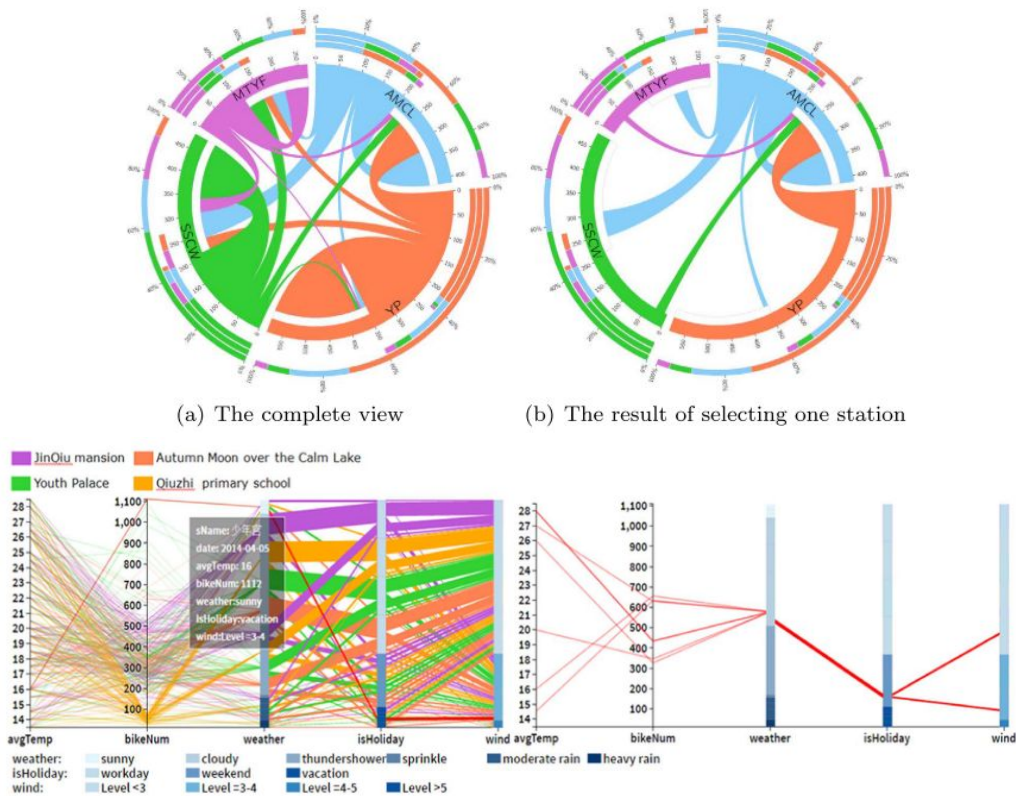


Figure 2.2.4: The visualization of flow exchanges between bicycle stations via a chord diagram (top), and the effects of contextual attributes (e.g. weather, holidays) on hire amounts of a particular station through a parallel coordinated plot (bottom). Source: Shi et al. (2018).

Shi et al. (2018) represent flow exchanges between bicycle stations (i.e. pick-up and drop-off actions) within a bike-sharing system (Figure 2.2.4 – top) using a chord diagram, where each station is represented as an arc with unique color. The arc length indicates the total flow magnitude of that station within the specified time period. The arcs are connected by ribbons, which thickness represents the flow magnitude exchanged between stations, and the direction is indicated by a white gap inside the arc. Finally, the peripheral three stacked bars provide comparative information on incoming and outgoing flows. This diagram is part of a VAS designed to explore flow exchanges and rental patterns of PBS data. The authors use a temporal heat map to represent the patterns of hire amounts per station over different days (y -axis) during the station’s opening hours (x -axis – from 6am to 9pm), and a coordinate parallel view (Figure 2.2.4 – bottom) to explore the effect of attributes such as climate condition, weather, and calendar events on hire amounts.

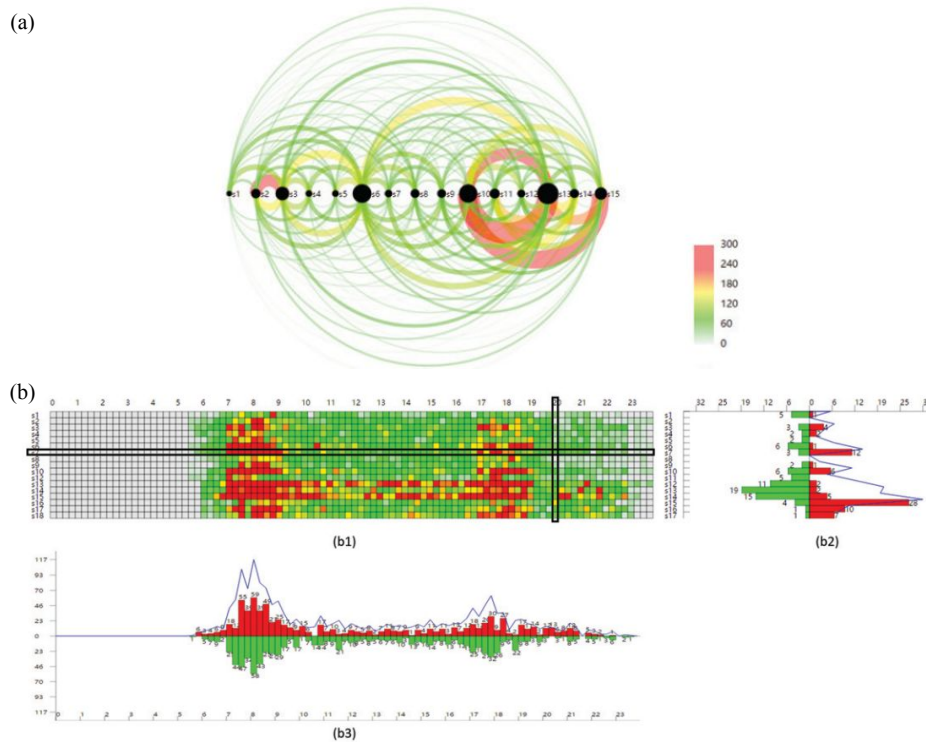


Figure 2.2.5: Visual exploration of bus passengers flow. The arc diagram (a) represents flow exchanges between pairs of bus stations, and the pixel-based chart (b) displays flow magnitude per bus station and time interval, which color encodes magnitude from red (high) to green (low). Source: Wang (2016).

Wang (2016) represent travel flows direction and magnitude between bus stations through an arc diagram (Figure 2.2.5a), which axis of circles represents the stations connected by ribbons, over or under the axis, according to the bus line direction. The circles size encode the amount of people getting on board of buses in each station, while the ribbons color and thickness encode flow magnitude between stations. The authors visualize traffic congestion at the road segment level through a line-route map, and flow volume for different bus stations via a pixel-based plot (Figure 2.2.5 – b1) at a time granularity of 15-minutes intervals. In both visualizations, color encodes traffic magnitude (i.e. red for high and green for low magnitude). Further, two bar charts (Figures 2.2.5 – b2-3) represent the flow magnitude of different bus stations at a particular time interval, and the variation of flow volume in a particular station along the day, respectively (red encodes people getting on board of buses and green otherwise).

Similarly, [Oliveira et al. \(2016\)](#) uses a pixel-based chart to represent bicycle rental over 24 hours at different days, months, or seasons of a year and according to diverse variables, such as bike and station availability, station capacity, bike return/rental counting and frequency. Subsequently, travel flows are represented per station according to trip distance and direction (i.e. incoming, outgoing and cyclic, which are trips starting and finishing in the same station), and considering the spatial context where the trips took place.

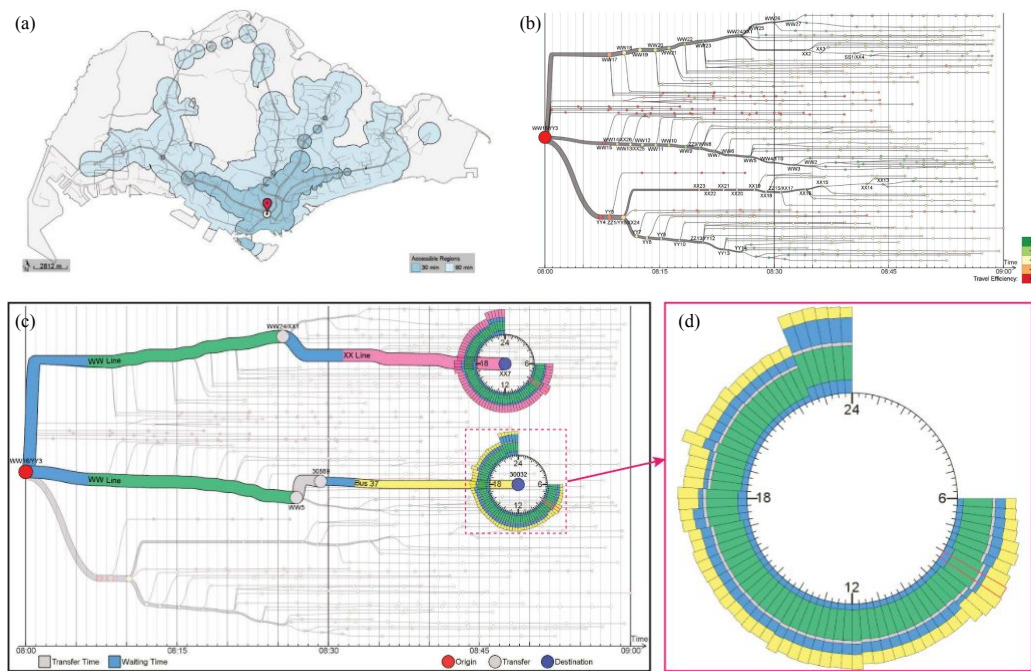


Figure 2.2.6: Visual exploration of mobility-related factors on a public transportation system. The *isochrone map view* (a) reveals the accessible regions from a particular location within a certain travel duration. The *isotime flow map* (b) visualizes mobility information along the time axis and clear pathways between O/D pairs. The *OD-pair journey view* (c) and the *mobility wheel* (d) display the temporal variation of waiting, transfer and riding times for a particular journey. Source: [Zeng et al. \(2014\)](#).

[Zeng et al. \(2014\)](#) visualize mobility-related factors (i.e. waiting, riding and transfer time, and travel efficiency) of a public transportation system. The proposed VAS comprises a *isochrone map view*, which presents geographical regions accessible within a certain duration from a given starting location (Figure 2.2.6a). The *isotime flow map view* represents journeys in a parallel isotime fashion with their corresponding travel time and efficiency indicated by the horizontal time axis and the nodes' colors, respectively (Figure 2.2.6b). The *OD-pair journey view* (Figure 2.2.6c) is revealed upon the selection of a

journey in the isotime flow map, which also enlarge the branches that forms the selected route and color-code different portions of the flow line to represent mobility-related conditions: light blue for waiting, gray for transfer, and standard colors of the public transportation lines. Further, the *mobility wheel* show the temporal variation of mobility-related factors around the clock by stacking small vertical bars representing each factor (Figure 2.2.6d), which summarizes the contribution of all factors together. Although the visualization allows to determine the efficiency of public transportation solutions by measuring the time one takes to travel between places, it does not support analyses based on the number of people are traveling between places and/or the amount of trips these people generate.

The *OD-Wheel* proposed by Lu et al. (2016) enables the exploration and comparison of O/D flow data over different locations (Figure 2.2.7). The technique sort O/D locations by traffic flow volume and place them along circular and linear axes. The rings represent different days and embed each a bar plot displaying the traffic volume of each region over the 24 hours. This same time axis is extended over the linear view, which detail either travel duration or traffic volume at each origin and destination.

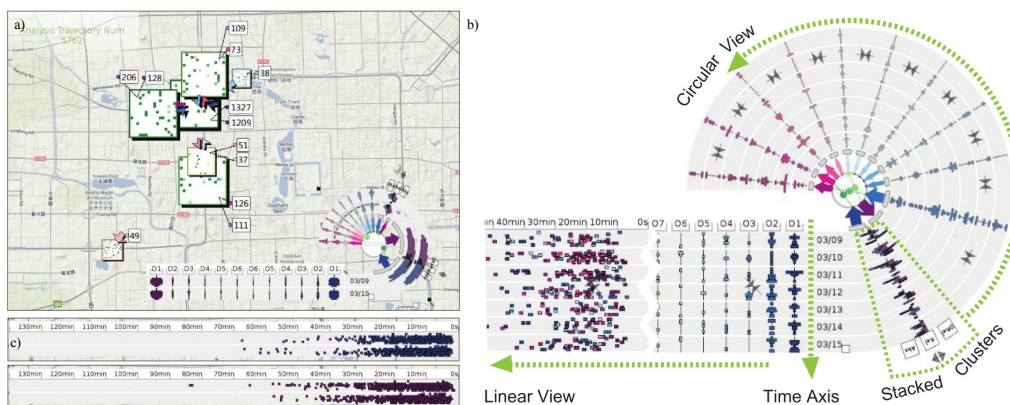


Figure 2.2.7: For a particular region selected on the map view (a), one can explore the incoming and outgoing flows dynamics over different days and time periods using the *OD-Wheel* (b). The detail view (c) displays the flow volume per travel distance along the day over a time granularity of 10 minutes. Source: Lu et al. (2016).

The Mobiseg system (Wu et al., 2017) visualizes latent activity patterns from taxi, metro and telco data, which datasets are separately treated to identify whether the activity (i.e. the action of arriving and departing) originate from taxi or public transportation. The geographical space is segmented into Voronoi cells, which embed glyphs that summarize the location's over-

all activity pattern (Figure 2.2.8b), while indicating whether it is an origin or a destination. Furthermore, an horizon graph along a circular time axis (Figure 2.2.8c) presents the temporal variation of different activity patterns according to the number of arrivals and departures.

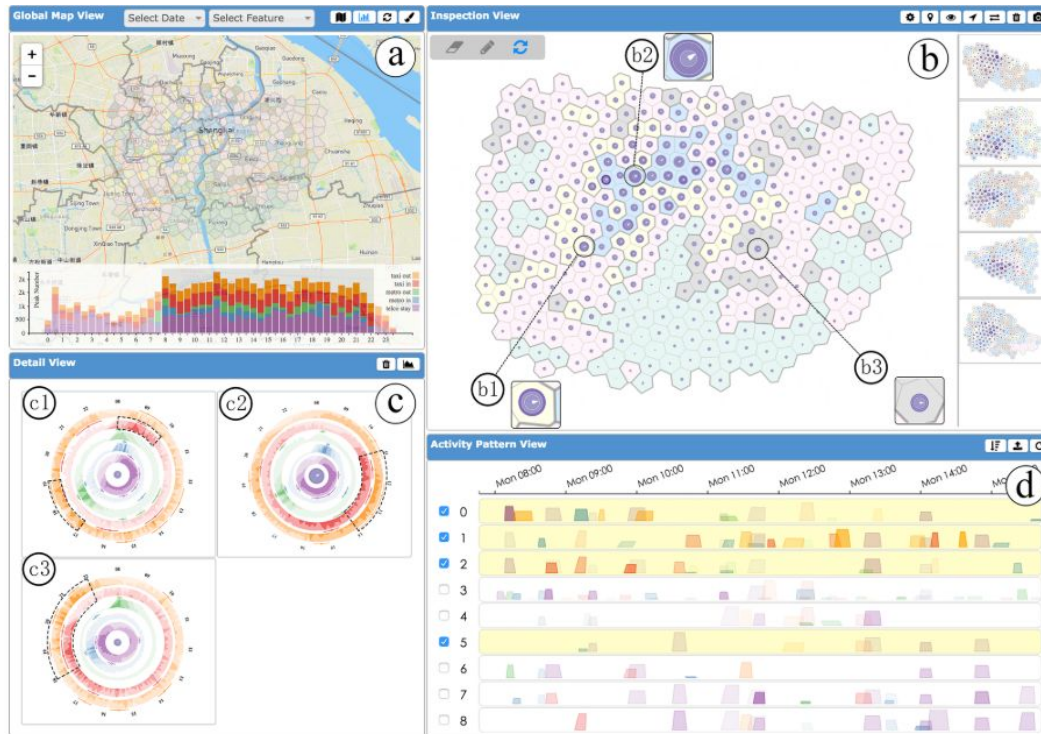


Figure 2.2.8: Visualization of latent activity patterns extracted from taxi, metro and telco data. Source: Wu et al. (2017).

Itoh et al. (2016) explore the effects of unusual phenomena (e.g., disasters, accidents, and public gatherings) in passenger flow within a metro system. The crowdedness of each train is estimated through the shortest time path for each trip (O/D pair). Upon the detection of an unusual phenomenon, the system estimates alternative routes possibly taken by passengers via external information regarding the train suspension (e.g., from the metro operating company or the transport information webpage). The temporal variation of unusual events over a particular day for one or multiple train lines is represented through a heat map (Figure 2.2.9a). The *Animated Ribbon* (Figure 2.2.9b) consists of a geographical map overlaid with animated 3D bands that represent the temporal variation of unusual phenomenon effects in passenger flow of each metro line. Semantic information explaining the situation is displayed on a *TweetBubble* view (Figure 2.2.9c), which gives an overview of keywords trends during the event.

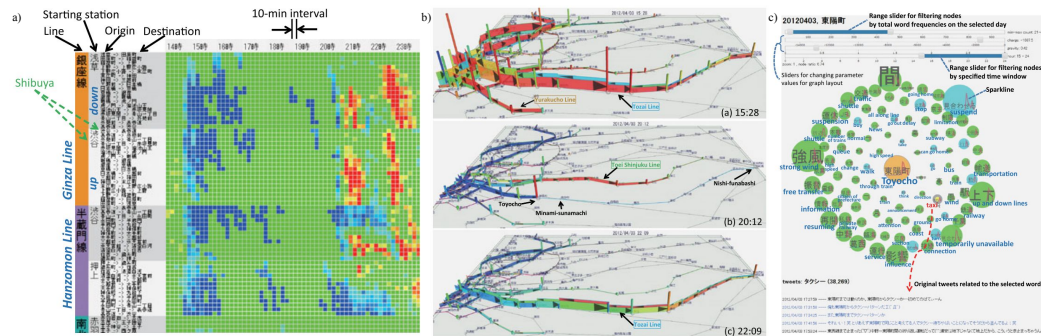


Figure 2.2.9: Visual exploration of unusual phenomenon effects in passenger flow within a metro system. Source: Itoh et al. (2016).

These contributions focus on improving the visualization of movement flow or supporting the analysis of certain aspects regarding urban mobility (i.e. usage and passenger behavior within biking-sharing and public transportation systems, and the effect of traffic incidents) via the visual exploration of travel flows. These visualization systems and techniques enable the representation of flows according to indicators of magnitude, speed, distance and direction, and their variation over space and time. However, we could notice that most approaches do not embed the spatial information in their flow visualization technique, but rather link geographical maps that indirectly provide the spatial information to allow the understanding of traveling patterns within the spatial context of the territory under analysis. We also observe that most approaches would focus on representing magnitude and distance, rather than direction, or at least the actual connections between different spatial locations. Further, they do not represent information regarding activities and transportation modes. Nevertheless, we will particularly explore the visualization techniques introduced by Shi et al. (2018) and Zeng et al. (2014) to represent flows and other travel attributes within our framework. In the following, we present previous contributions to the analysis of presence dynamics over time within urban areas.

2.2.2 Territory and Population Dynamics

Understanding the overall mobility patterns of a population is relevant to enable transport researchers to propose investments that are consistent with the spatiotemporal activity of an urban area across multiple temporal resolutions, i.e. the urban pulses resulting from human mobility (Miranda et al., 2016). In this spirit, Miranda et al. propose a framework to assist the visual explo-

ration of urban pulses across multiple cities under different conditions (e.g. weather, time of the day, or day of the week) through a geographical map and a timeline that shows the evolution of pulses at different locations over a temporal granularity of one-hour intervals. The UrbanFACET interface (Shi et al., 2017) allows to explore the spatial distribution of entropy-based mobility metrics according to POIs, regional demographics and population density in a metropolitan scale. One can select, filter and compare urban mobility patterns of different regions over a temporal granularity of 10-minutes intervals.

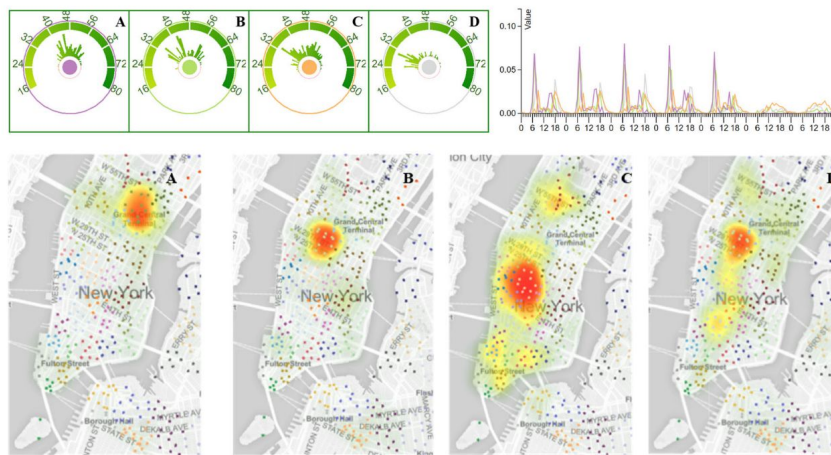


Figure 2.2.10: The geographical maps (bottom) display the spatial distribution of different activity patterns; the circular views (top left) represent the distribution of people per age group; and the line chart (top right) represents the temporal evolution of patterns. Source: Yan et al. (2018).

Yan et al. (2018) cluster bicycle *docks* of a bike-sharing system into spatial regions to explore the evolution of activity patterns (i.e. rental/return of bikes) along different days of the week, with a time granularity into one-hour intervals. The activity patterns are defined according to different spatial regions, time periods, and age ranges. For a particular activity pattern, a geographical map displays the spatial distribution of people (Figure 2.2.10 – bottom); circular views represent the age distribution through color intensity that encodes ranges of age (Figure 2.2.10 – top left); and a line chart presents the variation of different patterns over time, encoded by color (Figure 2.2.10 – top right). Likewise, Shi et al. (2015) visualize the spatio-temporal distribution of bicycle rental amounts. A map view displays every bike station as circles, which color intensity and size encode the number of rental or return. For a particular dock station, the temporal variation of rental/return amount can be compared over different days via a stacked area chart, and over one-

hour periods of a particular day via a bar chart. Both authors estimate spatial hotspots from bike rental amounts to indicate regions where people are present at different times of the day, which is possible due to the fact that most people would use bicycles for short trips. However, the data is not enough to describe the dynamics within a whole urban area.



Figure 2.2.11: Visual interface to explore the propagation of traffic congestion. The circles clear the locations where an incident occurred revealing the traffic conditions. The temporal variation of traffic can be explored via a timeline that gives the intensity of traffic incidents over time (bottom right). Source: [Anwar et al. \(2014\)](#).

[Anwar et al. \(2014\)](#) explore traffic flow data to reveal the propagation of traffic congestion induced by incidents over the network. An interactive map displays time-varying traffic flow and road incident data simultaneously. A 50% opacity mask is uniformly applied over the map to mute the color of major road segments (red for heavy traffic, green for fast moving traffic) so that the user's attention is fixed on the road incidents. Just before a road incident occurs, an expanding circle clears the mask over the location, thereby allowing the user to see how traffic behaves in the immediate vicinity of the incident. The circle's color encodes the incident's type: pink indicate accidents, blue reports heavy traffic, and orange signal vehicle breakdowns. The incident's duration (indication of severity) is proportional to the amount of time the circle stays open. Since it remains open until just after the event ends, users can compare traffic conditions before and after the incident occurred. Although the authors used data describing flows of vehicles, we classify this

VAS under territory and population dynamics since the displayed information correspond to the number of vehicles at different spatial positions and time moments, which allows to estimate where people are and for how long rather than where they are coming from and going to (i.e. our understanding of travel flows).

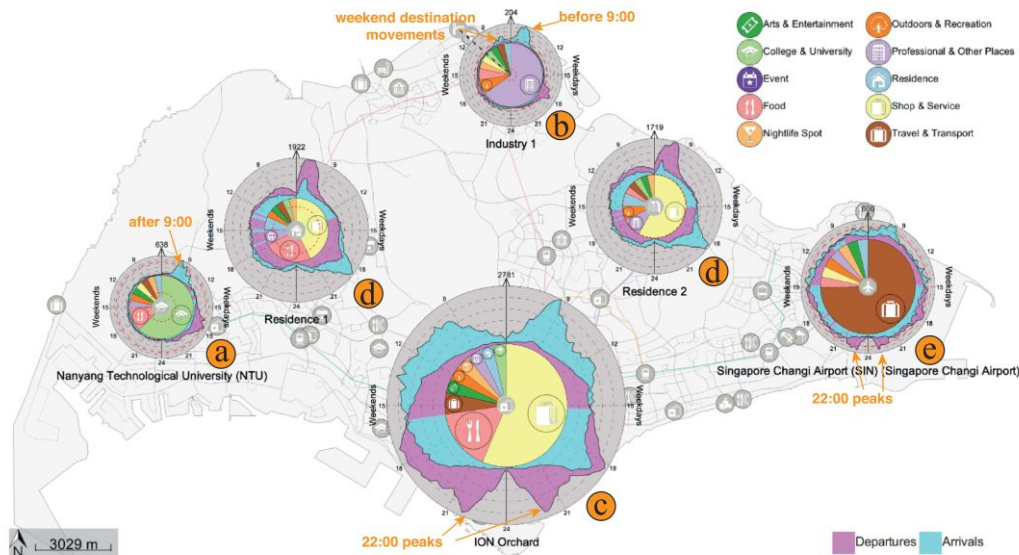


Figure 2.2.12: The visualization of POI-mobility signatures. The charts are placed on regions of interest, which displays the mobility intensity over different time periods by means of a stacked graph, and the activity context via a pie chart. Source: Zeng et al. (2017).

On the basis of a geographical map, Jahnke et al. (2017) explore the variation of hotspots and POIs spatial distribution over time. Hotspots are defined as areas with high concentration of taxi's pick-up and drop-off events, and the POIs are hotels, commercials, offices, restaurants, exhibition or business centers placed within a particular ratio from each hotspot location. Along the same lines, Zeng et al. (2017) visualize the POI-mobility signature of particular regions through the volume of departures and arrivals of people, and the activity context (i.e. available POIs in the area). A bivariate map gives an overview of the spatial situation, i.e. the density of departure and arrival of each public transportation station and the major POIs in the territory. The POI-mobility signature chart (Figure 2.2.12) provides further exploration of a particular region by displaying the variation of mobility intensity over time and the activity context. A central pie chart presents the distribution of POIs within a radius of 10-minutes walking distance (i.e. traveling speed of 5 km/h) from the region of interest. The stacked graph surrounding the pie chart dis-

play the number of people arriving and departing at different time periods encoded by color (i.e. aqua and pink, respectively). The temporal granularity can be customized to display the average mobility during weekdays, each day of the week, or the average over weekdays and weekends.

Inversely to what we have seen regarding the representation of flows, when representing presence dynamics, a geographical map is often the main visual component of the system, often linked to or overlaid by graphic diagrams that display complementary information (e.g., temporal or other). Particularly, we consider the POI-signature diagram proposed by [Zeng et al. \(2017\)](#) an interesting technique to represent the temporal variation of presence at a particular location, which we used as inspiration for visualizing certain indicators within our framework.

2.2.3 Individual Trajectories

The visual analysis of individual trajectories helps to understand the effects of spatial and socioeconomic constraints on the trips spatio-temporal shape and extent, and the daily activity schedules.

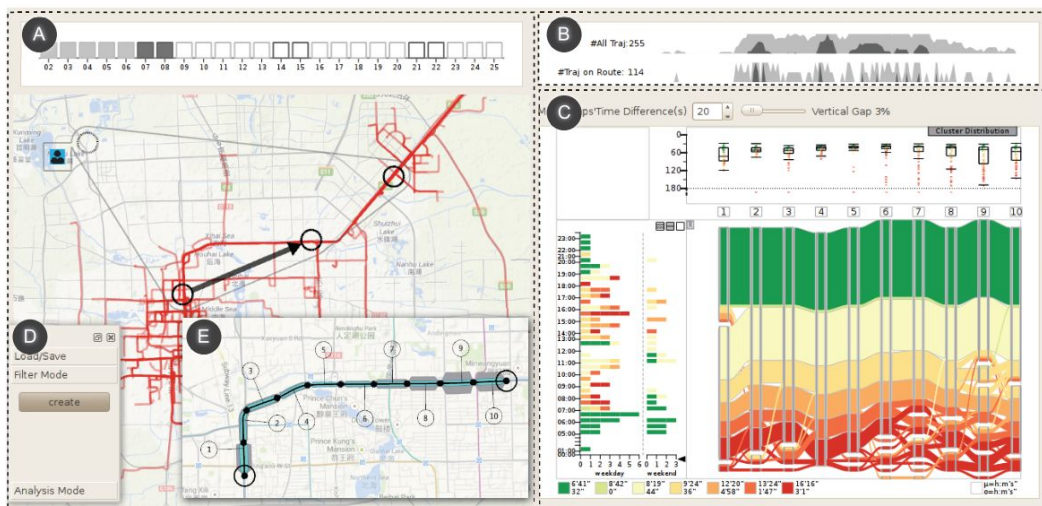


Figure 2.2.13: Ranking based visual analysis of taxi travel behavior. Source: [Lu et al. \(2015\)](#).

[Lu et al. \(2015\)](#) propose a ranking-based visualization to explore taxi travel behavior. On each road segment, the trajectories with similar duration are clustered together into groups, which represent different travel behaviors and

are ranked according to average duration. The user can configure filters and route segmentation via the spatio-temporal view (Figure 2.2.13A). The horizon graph displays the distribution of trajectories over a day (Figure 2.2.13B). The ranking view (Figure 2.2.13C) comprises a rank diagram of travel behaviors on multiple road segments; a temporal distribution of groups; and a modified box-plot that displays the average travel duration on each road segment.

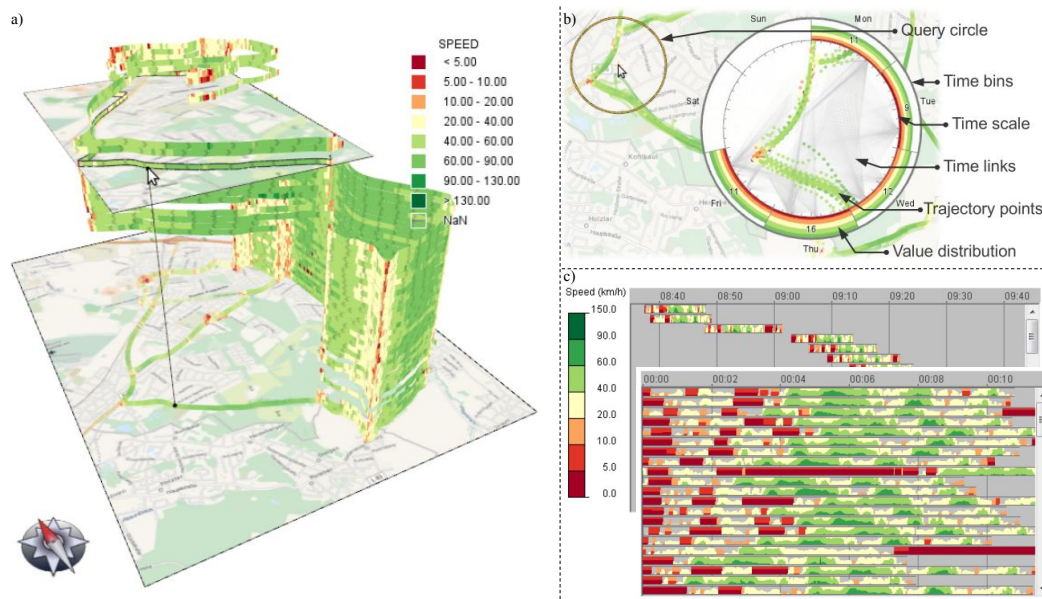


Figure 2.2.14: The TrajectoryWall approach. The individual trajectories are represented as stacked 3D colored bands on a 2D geographical map (a). The *time lens* (b) displays travel attributes aggregated on time according to a spatial query. The *time graph* (c) displays trajectories as stacked horizontal bands. Source: Tominski et al. (2012).

Tominski et al. (2012) focus on visualizing the thematic attributes of individual trajectories, which are represented as *color-coded bands*, and sets of trajectories by *stacking* these bands, which results on a 3D visualization where color-coded bands are stacked up on a geographical 2D map (Figure 2.2.14a). Their approach has been applied to taxi trip data, which travel speed is encoded by the band colors. The bands can be ordered according to the absolute times of the starts or ends of trajectories or according to their positions within a daily, weekly or seasonal temporal cycle. This ordering supports synoptic $S \times T \rightarrow A$ tasks (i.e. identify and compare one or many attributes over different locations and times) thanks to the human vision capacity to perceive relatively homogeneous colored spots throughout the stacked bands, which correspond to spatio-temporal regions of constant behavior. Likewise, grad-

ual changes of color along the horizontal axis indicate a spatial trend, while changes along the vertical axis suggest a temporal trend.

The TrajectoryWall supports spatial querying, which triggers an aggregate representation of attributes over time through the *time lens* (Figure 2.2.14b). The inner lens shows the trajectory points that match a circular spatial query. The ring is segmented into time bins (e.g., 4 quarters of the year, months, days of the week or hours of the day), which present for that query area: the number of trajectories intersecting it, their total duration, and the average time they were on that spatial region. Further, a 2D *time graph* (Figure 2.2.14c) displays individual trajectories as stacked horizontal bands, which provides a synoptic view regarding time, since overall temporal behavior can be characterized and searched for.

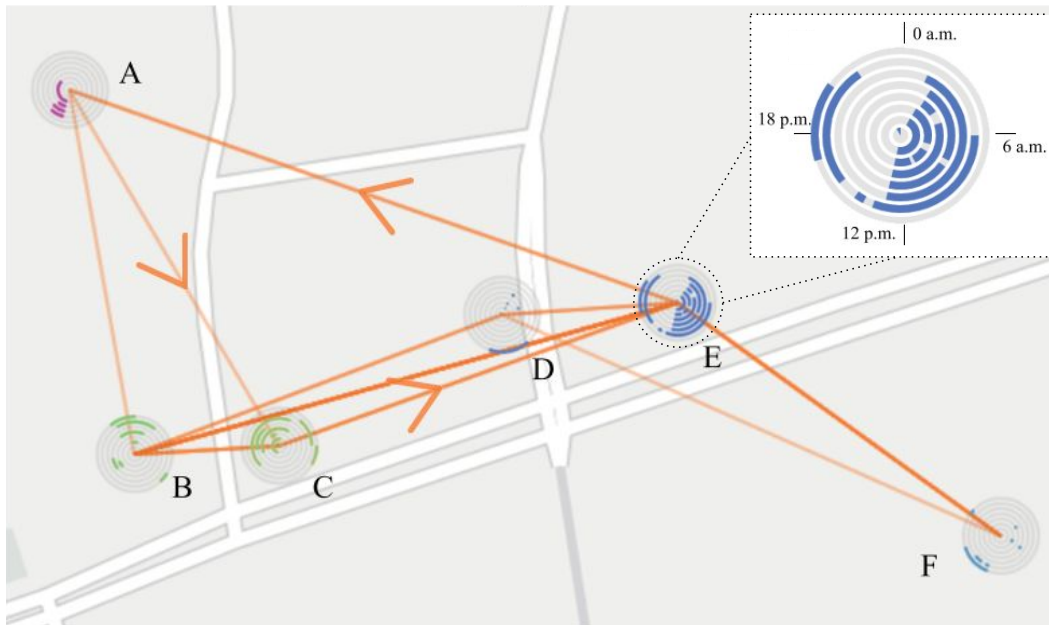


Figure 2.2.15: The spatio-temporal representation of individual trajectories in the *RelationLines* visual approach. The radial charts depict weekly movement behaviors of individuals, which colors encode activities performed in the spatial position of charts on the map. Source: [Chen et al. \(2018\)](#).

The *RelationLines* approach ([Chen et al., 2018](#)) merge five data sets (i.e. CDR, telco, taxi trips, check-in, and POI data) to explore egocentric networks among individuals who share similar locations or trajectories over space and time. These egocentric relations reveal how different persons connect and their connection degree, both socially and geographically. The spatial traces

are visualized on a road map overlaid by radial charts indicating the locations where people performed certain activities (Figure 2.2.15). Each ring of the chart represents a day of the week, which is segmented into 24 hours and colored to encode POIs and the action of traveling between places (gray).

Based on the premise that people with similar living and working environments have high probability of becoming friends, Zhang and Wang (2017) propose a visualization to improve online chat apps by revealing people's living and working locations. A heat map displays the spatial distribution of people living and working in the same regions, and with similar commuting time. A multi-ring donut chart supports comparison among daily behaviors of different individuals. Each person is represented by a ring, which are themselves segmented into 24 hours and colored to encode three activities: at home, on the road, at work.

Space-Time Cube (STC)

The STC is a powerful technique to simultaneously represent data in space and time, while enabling the visualization of thematic attributes. The interaction with the data is mostly based on 2D operations, as we can observe through the generalized space-time cube proposed by Bach et al. (2017), which comprises a descriptive model for visualizations of temporal data, transforming the cube's 3D shape into readable 2D visualizations. The model support operations such as extracting sub-parts of the cube, flattening it across space or time, and transforming the cube's geometry and content. However, this dependency can cause loss of information since the visualization must be simplified over a particular dimension (i.e. space or time), and can sometimes create visualizations that are hinder to interpret, such as the result of a space flattening operation on a base plane which coordinate system is not natural. The operation involves flattening the cube along a particular direction on the data plane instead of extracting a cut so that the final result can be read as a regular timeline.

The VISUAL-TimePAcTS system (Vrotsou et al., 2010) embeds a 3D activity-time cube, which represents activities, visited places and companionship as continuous trajectories (Figure 2.2.16). The y -axis represents time, the x -axis the individuals, and the z -axis depicts the activities. Color encodes seven categories of activities: care for oneself (green), care for others (turquoise), household care (pink), reflection/recreation (purple), transporta-

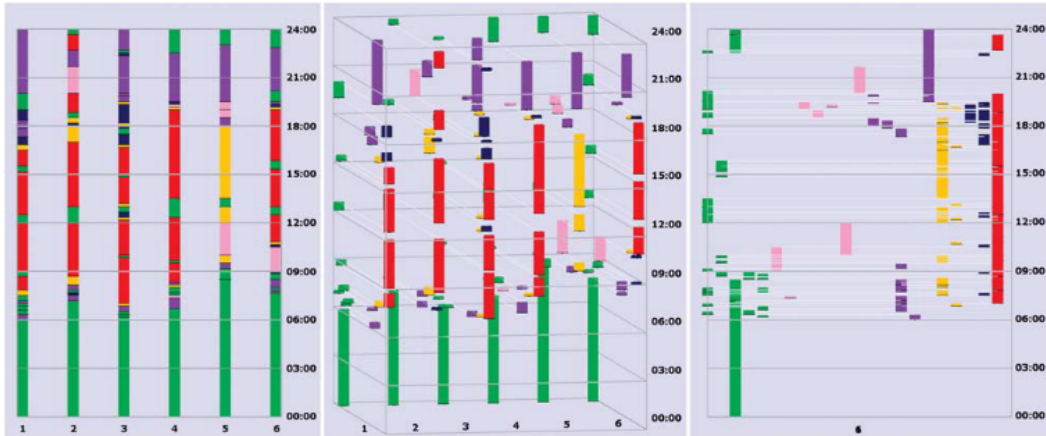


Figure 2.2.16: Visual representation of an activity-time cube of six activity paths. From left to right: front, rotated and side view. Source: (Vrotsou et al., 2010)..

tion (yellow), procure and prepare food (blue), and work/school (red). Basic interaction is provided for rotating, scaling and translating the cube.

The space-time GIS proposed by (Chen et al., 2011) supports exploratory analysis of activity data by generating space-time paths and providing a series of queries and analysis functions to investigate hidden activity patterns in an individual level activity diary data set. The analyst can filter space-time paths according to non-spatial attributes (e.g., gender, age, education, occupation and income), and spatial characteristics (e.g., residential location). The trajectories are colored to encode different types of activities, which helps to identify distinct characteristics of human activity patterns and facilitate the interactive visualization of individual and/or groups activity patterns (Figure 2.2.17a). Kernel density estimation is used to derive aggregate activity distribution surfaces at different time points, which comparison enable to explore the change patterns and find locations that gained or lost activities during the time period (Figure 2.2.17b). Further, the system provides a clustering method to group space-time paths of similar geometry, which could helps to identify useful activity patterns hidden in a large data set (Figure 2.2.17c).

Shoval and Isaacson (2007) use a method of sequence alignment for analyzing the sequential aspects of human activities within the temporal and spatial dimensions (Figure 2.2.18). The geographical area is divided into polygons, which are coded by single characters. The temporal dimension is represented by sequences coded using an equal amount of time per character, which captures the time spent in each location. This approach can be used to recognize

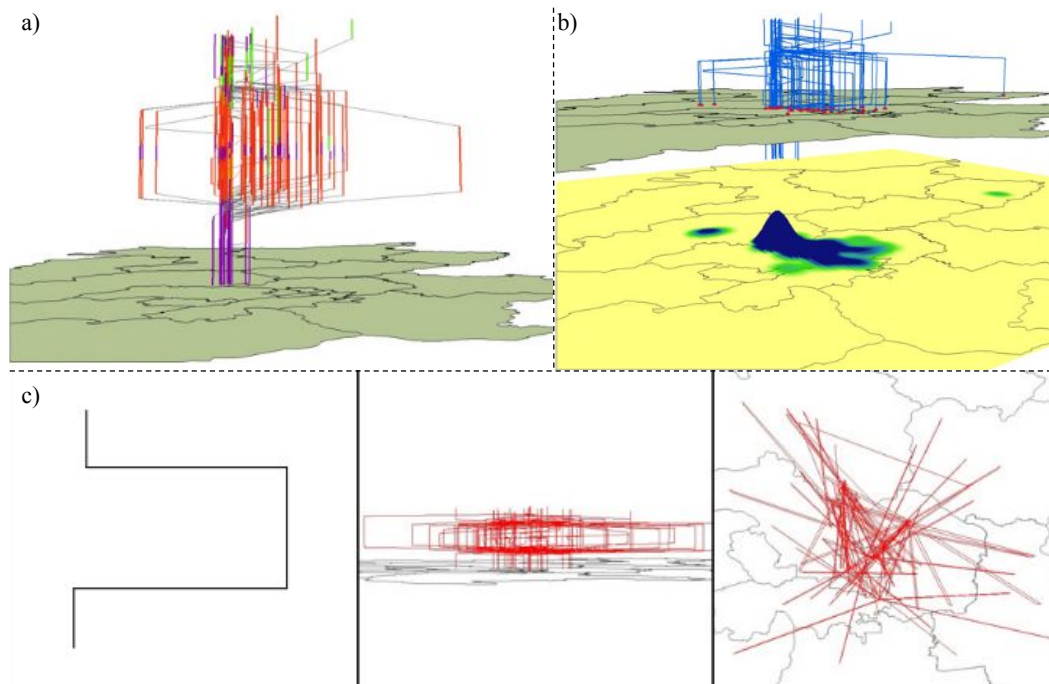


Figure 2.2.17: The individual space-time paths are colored to encode different types of activities (a). A kernel density estimation algorithm reveal aggregate activity distributions surfaces at different time units (b). Space-time paths are clustered together based on their similar geometry (c). Source: [Chen et al. \(2011\)](#).

common sequences of elements that appear in a large database describing spatial behavior. However, contrary to the previous STC representations, this visualization does not support semantically enriched trajectories, i.e. one cannot know why and/or how people traveled between places.

To overcome the drawbacks of STC, [Gonçalves et al. \(2016\)](#) propose to combine a 2D map and a 3D STC to explore spatiotemporal trajectories (Figure 2.2.19), which they found to be advantageous for simultaneously analyzing spatial and temporal information, and although users liked the map better, the STC provided more accuracy in spatio-temporal tasks. Likewise, [Kveladze et al. \(2015\)](#) study the usage of a visualization system that combines a map, parallel coordinates and multiple instances of the STC, enabling the simultaneous exploration of different perspectives to the data (i.e. time, space, and individual characteristics) to study the movement of suburban commuters in Tallinn. Users found useful to switch between 2D and 3D views, while the parallel coordinate plot was not really used. Both systems support simple interaction (pan, rotate, zoom in/out) via a traditional mouse device.

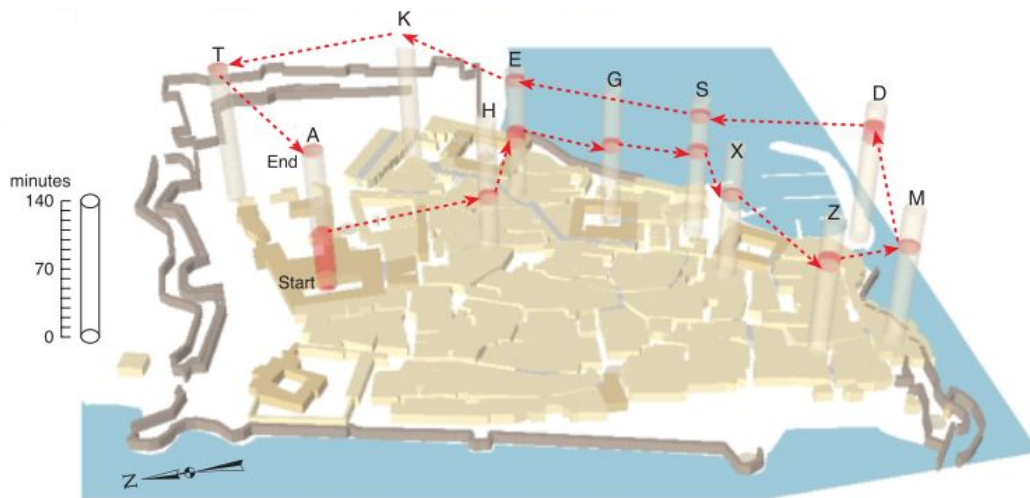


Figure 2.2.18: Typical space-time paths visualized through a sequence alignment method. The vertical pillars represent the stops of an individual, which height encodes the duration of the individual's trajectory and red segment encodes the time they spent there. Source: [Shoval and Isaacson \(2007\)](#).

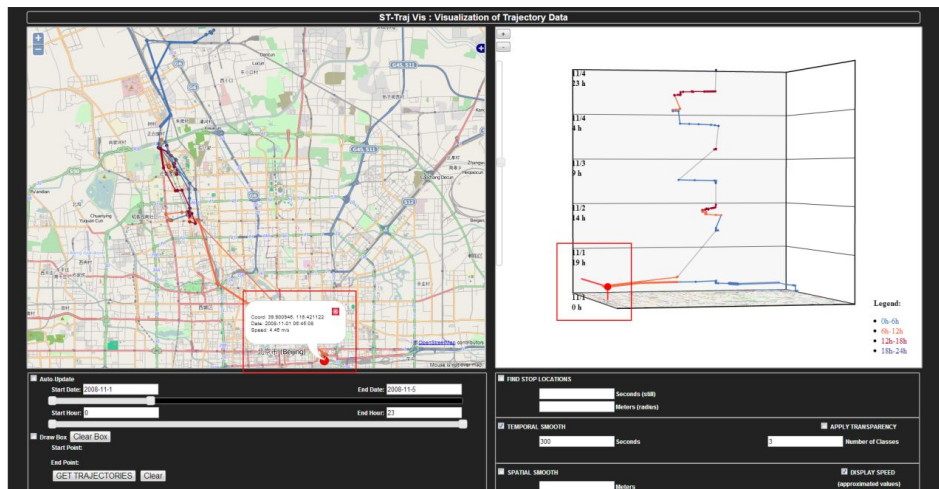


Figure 2.2.19: Visualization of trajectory data using both the STC and a geographical map. Source: [Gonçalves et al. \(2016\)](#).

Whilst there are a few approaches that combine multiple 2D visualization techniques, we observe that most authors would employ 3D visualization techniques to represent multiple dimensions of the data, which is unavoidable when representing trajectories, since their evolution occurs simultaneously in space and time. Furthermore, contrary to the aforementioned visualizations of flows and presence dynamics indicators, these approaches focus much more

on representing the attributes that describe the trajectories, either related to the trip (e.g., speed) or to the individual (e.g., activities, socio-demographic aspects). We can notice that using 3D visualization is advantageous to represent multivariate data when they are combined to other techniques, specially a geographical map to provide spatial information.

2.2.4 Multiple Objects of Interest

Up to this point, we presented VASs that enable the analysis of urban mobility based on indicators derived from a single object of interest, which can provide insights to certain aspects of the urban mobility phenomenon. For instance, one can understand the exchanges between places resulting from individuals' trips, or the evolution of the territory according to who visited it and why, or yet how the activity programs of individuals influence their need for traveling. However, one cannot cross those information to understand the whole scenario underlying the urban mobility phenomenon. Therefore, we focus hereafter on VASs that enable the analysis of urban mobility data via the simultaneous exploration of indicators derived from more than one object of interest.

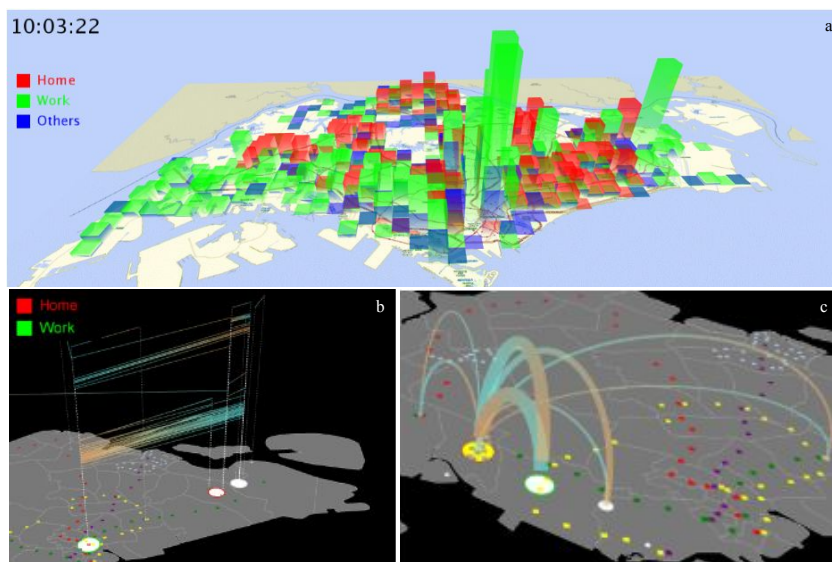


Figure 2.2.20: The iVizTrans interface. The spatial distribution of people according to their activities (home, work, others) at 10am (a). The spatio-temporal visualization of individual commuting trips (b). Travel flows from home to work locations (c). Source: Yu et al. (2015).

The *iVizTrans* system (Yu et al., 2015) allows the analysis of travel flows, territory dynamics (Figure 2.2.20a) and individual trajectories according to thematic attributes describing home and work locations. The system combines spatiotemporal visualization and machine learning techniques to learn from human users and apply knowledge to automate the classification of smart card data records revealing commuting patterns and, consequently, home/work locations. The visualization represents spatial and temporal attributes of movements and trips' O/D locations, while highlighting the important locations and the dominant travel patterns. For a particular region, a 3D arc diagram reveals the incoming and outgoing flows (Figure 2.2.20c). Trips are displayed in a space-time cube, where they may be explored individually or clustered to remove random trips and retain only the ones with recurrent patterns (Figure 2.2.20b).

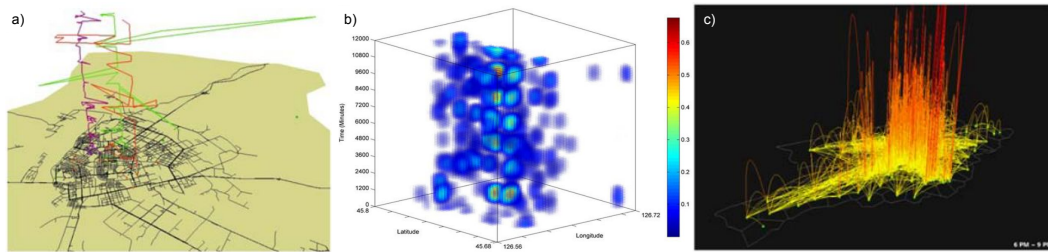


Figure 2.2.21: Spatio-temporal visualization of individual trajectories (a), hotspots of human activity (b), and flows of information or movement (c). Source: Gao (2015).

Gao (2015) proposes a processing and analytical framework that integrates spatio-temporal visualization, kernel density estimation and auto-correlation analysis for exploring dynamic mobility and intra-urban flow patterns (Figure 2.2.21). Their approach enables the visualization of individual space-time paths (i.e. a person's mobile tracking in space over a week), spatio-temporal hotspots of human activity (i.e. phone calls), and flows between O/D locations (i.e. the call interactions between mobile cells in different time moments) by means of magnitude, direction, distance and duration. A 3D flow visualization using vertical Bézier curves provides interactive visual exploration of information or movement flow between places, which variation over time is supported via multiple time snapshots or continuous animation.

Chen et al. (2015) visualize movement patterns from check-in data enriched with semantic information describing travel purposes and transportation modes. The former is estimated from the number of people geographically co-located, and the latter from a combination of distance and timestamp of

online posts at different locations. The temporal distribution of check-ins at each POI is represented through a radial chart on a geographical map (Figure 2.2.22b), which rings have each two histograms at opposite directions, encoding movements in and out the place. Bar charts display the temporal distribution of check-ins (Figure 2.2.22e), while a pixel-based chart presents the intensity of movement at different travel distances and duration (Figure 2.2.22c). Travel flows and individual trajectories are visualized via directed line segments in the central map area of the radial chart, and through a line-based chart (Figure 2.2.22d), where travel duration and distance are simultaneously represented in opposed sides of the y -axis. The user can customize time granularity as 24-hours or 7-days intervals.

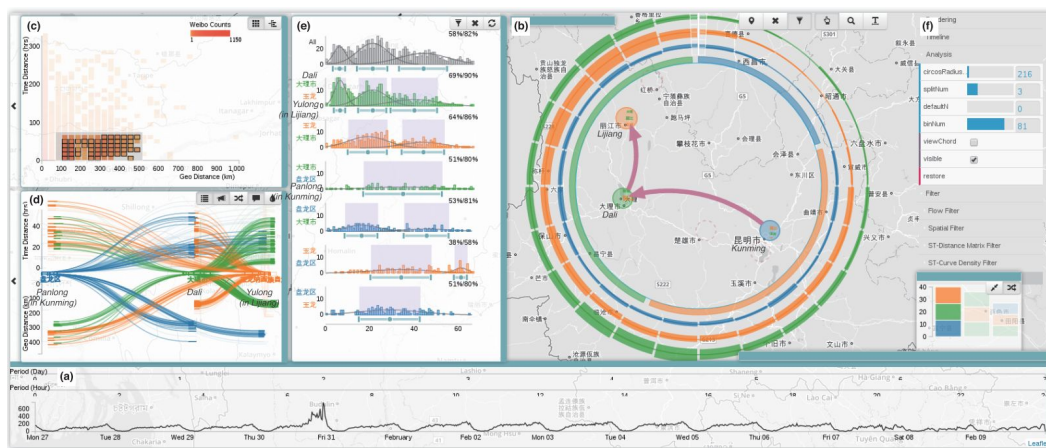


Figure 2.2.22: A visual analytics system for exploring sparse microblogging data. Source: [Chen et al. \(2015\)](#).

The Mobiliscope ([Le Roux et al., 2017](#)) uses household travel survey data to explore segregation of various social groups in the same urban areas over 24 hours. The system supports comparison of “night-time” (residence-based) and “day-time” (activity-based) measures of segregation, and identification of the most segregated group or the areas with substantial changes in their population’s social composition. The visual interface (Figure 2.2.23) comprises an animated map view, where the number/proportion of people present at each location can be explored per one-hour interval over a day; the line chart presents the temporal variation of the segregation index over 24 hours; and a stacked chart displays the temporal variation of people present in a particular location over 24 hours. The statistical indicator represented in these charts is calculated according to a particular variable, such as activity, mode of transport, age, household income, education level, and so on.

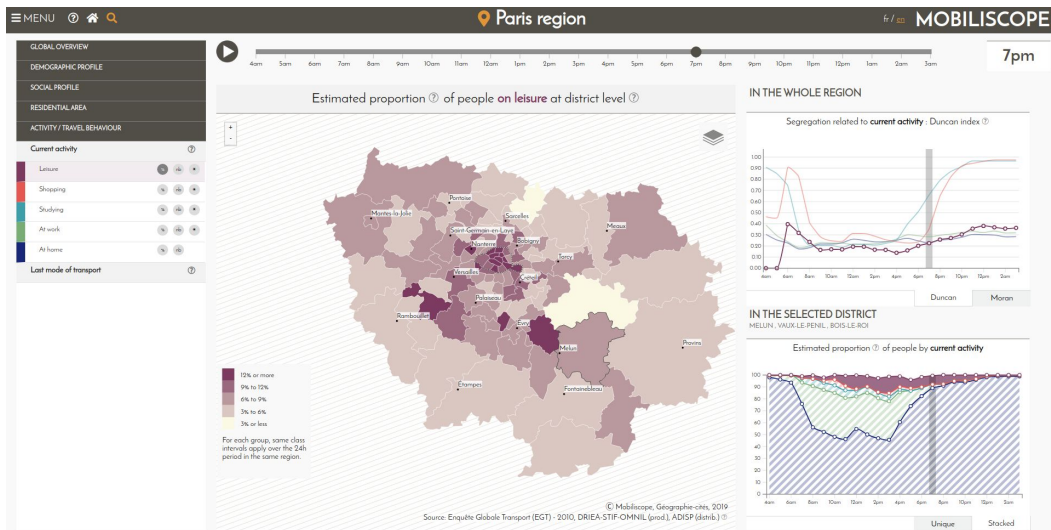


Figure 2.2.23: The Mobiliscope (Le Roux et al., 2017), a visual analytical system for studying social segregation. Source: Snapshot from <https://mobiliscope.parisgeo.cnrs.fr/>.



Figure 2.2.24: The TelcoFlow visual interface. Source: Zheng et al. (2016).

Zheng et al. (2016) propose a visual interface to explore the collective behavior of people by analyzing different perspectives of the data. The Multi-facet Filter view (Figure 2.2.24a) supports dynamic aggregation and filtering

of data over space and time according to population type, activeness and correlations. The flow river-based chart displays the variation of states (i.e. POIs) over time (Figure 2.2.24b), which reveals the linear evolution of state clusters, cluster merging and splitting. Colored stripes represent state clusters, which height encodes the number of people at that state over each time period. The stripe can either split into several branches when people's states become diverse, or merge with other branches when people get into similar states. A particular state can be further explored through the stacked radial chart (Figure 2.2.24d), which time people spent in that state and the distance traveled after their departure can help to estimate where they came from. The layers' height encodes the number of people at that state cluster and color intensity inversely encodes distance (i.e. darker purple means shorter distance).

The VAS proposed by Wang et al. (2017) enables the exploration of movement flow and presence of people at different locations and time periods, which can be a single time slot of 60 minutes or multiple periodic time slots. The space is segmented into voronoi cells based on the geographical position of base radio stations. On the top of a multivariate map, movement flows between locations are displayed by means of directed lines, while a heat map display population density at different locations and time periods. Further, the temporal variation of population flow for different speeds is visualized via a stack graph. Wang et al. (2013) use pixel-based charts and line-route maps to represent traffic congestion at the road segment level, which visualization aims to reveal relationships between traffic jams, while identifying whether an event was caused by or has led to any other event.

The co-presence of individuals (i.e. the simultaneous presence of different people in the same geographical location) can reveal phenomena such as the attractiveness of certain geographical regions and the social segregation throughout an urban territory over different time intervals. Wu et al. (2015) use two linked geographical heat maps to represent the spatial distribution of incoming and outgoing flows. Thereby, a high density of incoming flows indicates that people from different locations co-occur there (Figure 2.2.25b), while a high density of outgoing flows indicates that people from this location would likely co-occur with others elsewhere (Figure 2.2.25a). A contour-based tree map view (Figure 2.2.25d) displays the variation of people present in a particular place over time, the distance to where these people come from, and the visit frequency per region. The chart represents time ranging from 6am to 10pm at a two-hour granularity on a circular axis, which time slices comprise a contour line detailing distribution of people visiting the place at a finer time

granularity. Each time slice is filled out with rectangles representing the space, which size and color intensity encode the number of people present and the distance where they come from, respectively. Further, a Parallel Coordinates (Figure 2.2.25e) and an Extended LineUp (Figure 2.2.25f) charts are used to quantitatively analyze biclusters (i.e. bundled origins and destinations of people) over multi-varied attributes and to explore their diversity.

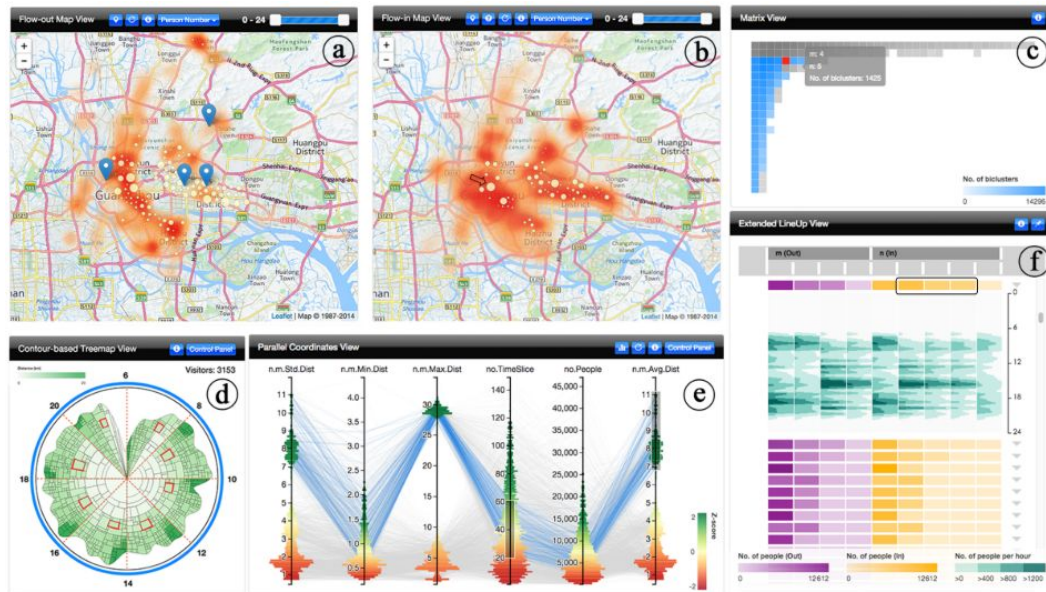


Figure 2.2.25: The visual interface of TelCoVis. Source: Wu et al. (2015).

2.2.5 Synthesis

This section summarized the contributions made by thirty-five publications to the visual analysis of urban mobility data, classified according to the addressed object of interest. The surveyed studies mostly focus on exploring specific issues of urban mobility analysis, particularly regarding urban traffic flows and monitoring, people dynamics in an urban environment, road traffic accidents (Sobral et al., 2019), and more recently, the usage of bike-sharing systems, which not necessarily addresses the reasons that drive human mobility (see Table 2.2.1). Figure 2.2.26a shows that twenty publications provide visualization of travel flows and trips, sixteen represent the territory dynamics through the variation of presence of people at different spatial locations and time intervals, and thirteen represent data at the individual level (i.e. trajectories of people).

ID	Reference	Topic
1	Yu et al. (2015)	people dynamics in urban areas
2	Gao (2015)	travel patterns
3	Chen et al. (2015)	sparse trajectory data
4	Tominski et al. (2012)	traffic analysis
5	Lu et al. (2015)	travel behavior of vehicles
6	Zhang and Wang (2017)	passenger behavior in PTS
7	Chen et al. (2018)	egocentric relationships
8	Gonçalves et al. (2016)	spatiotemporal trajectories
9	Kveladze et al. (2015)	commuting patterns
10	Vrotsou et al. (2010)	activity patterns
11	Chen et al. (2011)	activity patterns
12	Shoval and Isaacson (2007)	spatiotemporal behavior
13	Le Roux et al. (2017)	social segregation
14	Zheng et al. (2016)	co-occurrence
15	Wang et al. (2017)	people dynamics in urban areas
16	Wang et al. (2013)	traffic jams
17	Jiang et al. (2015)	travel patterns
18	Wu et al. (2015)	co-occurrence
19	Shi et al. (2017)	people dynamics in urban areas
20	Miranda et al. (2016)	urban pulse
21	Yan et al. (2018)	PBS usage
22	Jahnke et al. (2017)	people dynamics in urban areas
23	Shi et al. (2015)	PBS usage
24	Zeng et al. (2017)	activity patterns
25	Zeng et al. (2014)	travel behavior in PTS
26	Shi et al. (2018)	PBS usage
27	Itoh et al. (2016)	passenger behavior in PTS
28	Lu et al. (2016)	travel demand
29	Wang (2016)	travel patterns in PTS
30	Wu et al. (2017)	activity patterns
31	Oliveira et al. (2016)	PBS usage
32	Anwar et al. (2014)	traffic incidents
33	Andrienko et al. (2016a)	trip patterns
34	Boyandin et al. (2011)	migration
35	Yang et al. (2016)	people and resources flows

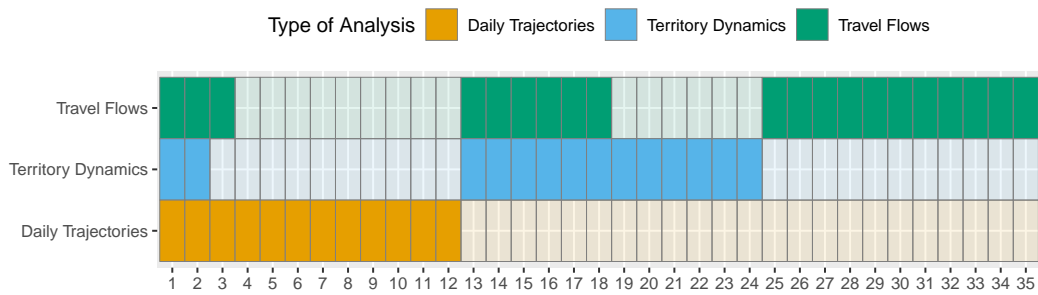
Table 2.2.1: Surveyed publications according to the urban mobility issue they address.

Although human mobility seems to be evenly described from every perspective, most solutions providing the analysis of more than one object of interest would often combine travel flows with territory dynamics, since both analysis are done at the population level, or travel flows and daily trajectories, since the former result from the aggregation of single trips. Only the solutions proposed by Gao (2015) and Yu et al. (2015) enable the analysis of urban mobility data via the exploration of all three object of interest. Both solutions employ 3D visualization techniques to represent the information in space and time simultaneously, while including the possibility of representing thematic attributes, such as trip purposes. Firstly, 3D visualizations that support interaction via 2D operations have issues such as occlusion and loss of information. Secondly, both systems present certain restrictions regarding the extent to which each object is addressed within the system and the freedom one have to explore the information.

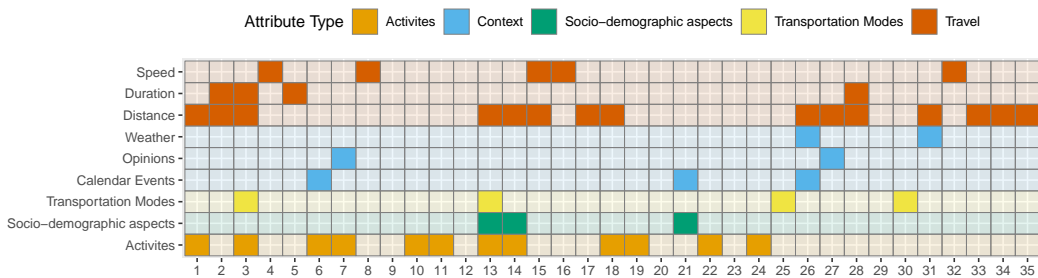
One can analyze the population and territory dynamics through the variation of people estimated presence over time at different spatial locations. The iVizTrans system (Yu et al., 2015) also allows to identify work and home places, which range of activities could be easily expanded by modifying the recognition algorithm. Further, when exploring flows and trajectories, one can only visualize connections between places of work and residence of people, which allows one to understand where people work and live, and how far one travel to perform these activities. Nevertheless, this segmentation of daily trajectories into trips between home and work locations prevent one to obtain information about where people were located in between trips and what types of activities they were performing (e.g., whether they stayed at the workplace during the whole day, or went for a walk, lunch or sport activities). In the framework proposed by Gao (2015) the visualization of flows is clearly cluttered by the amount of data, and the geographical information can only be recovered through latitude and longitude coordinates, which without being associated to a geographical map is not intuitive to users.

Thematic attributes are often represented, yet they are either derived from the spatio-temporal dimensions of data to describe trips via attributes such as speed, distance and duration, or external, such as calendar events and weather information. There is about one-third of papers (1, 3, 6, 7, 10, 11, 13, 14, 18, 19, 22, 24) that explore mobility according to activities, from which the majority (except 10, 11, 13) are estimated POIs from the combination of geographically co-presence of individuals and external data. Further, the activity information would often be used to describe individual trajectories or territory dynamics.

Transportation modes are difficult to represent because the data frequently originate from a type of transportation system, such as bike-sharing and taxis, which transportation mode is intrinsic to the data and invariable. Smart card data provides information on people movement within the PTS system, where different modes of transport, such as metro, train, and bus, could be identified. This information could help transport planners to understand how people use the city's PTS and on which types of public transportation make investments. Moreover, in social media and mobile phones data (e.g. CDR and telco data) the transportation mode is unknown. Thus, this information is hardly explored, except when using survey-based data, where individuals explicitly inform the used transportation for every trip, or combining different data sources to estimate travel modes. We identified three papers that describe transportation modes using estimation methods. A fourth publication (13) uses data from a household travel survey, where this information is explicitly provided by the interviewed people.



(a) Types of analysis.



(b) The thematic attributes.

Figure 2.2.26: Distribution of surveyed papers according to types of analysis they support and thematic information they represent. Source: the author.

The majority of surveyed papers addresses the analysis of human mobility from the aggregate level, which reveals movement patterns of a whole population based on indicators that describe the territory and travel flows.

Particularly, we observed that flow analysis is often supported through the counting of trips at origins and destinations or along road segments, which gives the magnitude or density of flows. These indicators have been used in the literature to reveal the spatio-temporal dynamics of human movement, while highlighting the attractive locations at different time intervals. This information is also used to detect co-presence of individuals, since a high density of incoming flows in a particular location likely indicates that people from other locations co-occur there. Nonetheless, flow orientation is equally important to understand where people come from or go to, which helps to explain how the different locations are connected within a territory.

In order to represent flow direction without losing the spatial dimension and avoiding the well-known *spaghetti effect*, authors would combine maps and geometric visualizations such as linking origin and destination maps through arrows connected to cells of a shading matrix. Other approaches would simply provide diagrams where the connection between O/D locations is unambiguous, without representing the spatial information. Although both approaches have a great potential to display O/D flows, the former would require a large visualization space and the latter would have to be somehow combined with maps to transfer more meaningful information.

Regardless the spatial layout of visualization components, the VASs we surveyed share the aspect of being designed over a CVV paradigm, which enable them to combine complementary techniques to visualize the multiple dimensions of data. Particularly, the authors often employ the juxtaposed layout (CMV) due to the independence among views and little visual cluttering, which are both relevant aspects to explore movement data, since it requires the derivation of various complementary measures that are not necessarily dependent from each other. Plumlee and Ware (2006) showed that multiple views are advantageous when visual comparison involves items of a greater complexity than what can be held in visual working memory, because the latter can only hold one graphical object at the time in comparisons tasks mediated by eye movements, which means that mitigating the load on visual memory helps to reduce errors.

Furthermore, the visual analysis procedure embedded in the surveyed VAS follow a well-known mantra consisting of *overview, zoom and filter, then details-on-demand* (Shneiderman, 1996) to explore different perspectives of a data set. Despite the rise of technology and the surge of new interactive visualization techniques, maps continue to be a powerful tool to represent the geographical space. Therefore, we usually find them as the central view in

a visualization environment, which provide overview to the situation before an in-depth analysis of the phenomenon within a specific location or set of locations.

The temporal variation of indicators is often explored through continuous animation, composite visualizations connected via *linking and brushing* interaction techniques, or temporal matrices, which displays the whole data at once for every time period. The latter have been often used to represent flow magnitude either at a certain location (i.e. incoming or outgoing flows) or between pairs of locations. Either way, the columns would represent different time intervals, while the rows would correspond to a location or pair of locations, and their intersection would be color-coded to represent the magnitude values. Since urban mobility patterns present little variation over similar days, particularly over weekdays, it is common to observe cyclic representation of time to represent these repetitive patterns every 24 hours. In this context, the temporal information is commonly combined with space by overlaying a timewheel-based visualization over a particular location, which summarizes the temporal variation of a particular mobility indicator for that spatial location.

The interactive visualization supports filtering methods to subset the data according to semantic, spatial and/or temporal attributes, depending on the dimensions supported by the analysis. Selection, zooming, panning, and brushing and linking are typical operations supported to enable deep exploration and comparison of data, while highlighting the relevant information to keep the user's attention at the right place at the right time. Some systems support visual querying by allowing users to draw circles or other geometric shapes on the map, which spatial region serve as input for the query. Further, a few visualizations allow users to modify the spatial and temporal granularity, such as changing the territorial segmentation or the extent of time intervals.

Among the VASs, only one system uses a device other than mouse and keyboard for interacting with the visualization, which is displayed on a large, high resolution screen and interactively explored via a touch pad. We observed that the combination of large visualization spaces with tactile and tangible interaction can be beneficial for exploring large datasets, while making the user experience more engaging.

The topic of non-conventional interaction has a particular importance within our approach due to our choice of using multiple and possibly large displays to explore urban mobility data. Although CMVs have been shown

to be effective and are widely used in visualization, they present views side-by-side, therefore restricting the screen space that can be allocated to each view. Therefore, the natural approach to overcome the screen space limitation is to use large high-resolution displays (LHRD), which allows to display more data and details, while leveraging spatial memory and facilitating collaboration. Nonetheless, one cannot simply scale up visualizations or display more data, but rather adopt a more human-centric perspective (Andrews et al., 2011), which also implies on designing interaction interfaces that are more adapted to these displays than the traditional mouse and keyboard, for instance. Thereby, the next section presents alternative approaches that use LHRDs or combine multiple conventional displays to improve the exploration of multi-dimensional data using CMVs, and explore the potential of mobile devices as visualization and interaction tools to explore data over these alternative displays.

2.3 Non-conventional Displays and Interaction Techniques

This section focus on the advantages and limitations of using large, high resolution displays or multiple display to visualize large and multidimensional datasets. Further, we explore the possibilities of using handheld devices as intermediary apparatus to interact with these non-conventional displays.

2.3.1 Large, High Resolution Displays

There are numerous applications within information visualization that leverage large, high resolution displays (LHRD) to explore data at human-scale physical sizes, where large amounts of data can be simultaneously visualized through a great number of pixels (Ni et al., 2006). Andrews and North (2012) stated that a flexible spatial environment encourages the adoption of incremental formalism and exploration, and that using detailed representations and visual links to highlight connections in the workspace reduce cognitive bias by reducing the reliance on memory. Rajabiyazdi et al. (2015) showed that the combination of size and resolution of large displays support the discovery of new information within a data set previously explored on conventional displays.

To ensure the use of advantages offered by these displays, [Andrews et al. \(2011\)](#) drew attention to the fact that LHRDs are human-scale environments defined more by the abilities and limitations of the user than by the technology, which implies that one cannot simply scale up existing visualizations or display more data, but rather adopt a more human-centric perspective. The authors propose yet a set of guidelines regarding aspects of visual encoding, visualizations adaptation, large data displaying, graphic scalability of encoding and visual representation, navigation techniques, selecting and marking, to improve the design of applications for LHRDs.

Human-computer interaction (HCI) techniques are intrinsic to information visualization, enabling the user to deepen data exploration and ensuring user performance in visual analysis. In this context, the democratization of smartphones has opened up research opportunities within diverse branches of HCI, seeking to improve distant and wireless interaction while leveraging tangible and tactile input. Particularly, we observe their use as interaction devices in visualizations of large amounts of data on LHRD, where the traditional interaction through mouse and keyboard might not be efficient (or comfortable) to exploit the potential of these large displays.

In this context, [Bezerianos and Isenberg \(2012\)](#) suggest the viewer should stand far away from the display to conduct tasks that require perception, and in case the tasks need to be conducted close to the display, the important information should be placed directly in front or above the viewer, who should also receive an estimation of distortion effects or be encouraged to physically “navigate” throughout the display in specific ways to reduce judgment error. [Langner et al. \(2018\)](#) used a large scale CMV visualization interface that supports interaction through the handling of a tracked mobile device and direct touch on the display (Figure 2.3.1), to show that users associate movement positively and often move varying their distance to the display, stand and walk close to each other most of time, and use natural, non-digital interaction such as pointing fingers.

In the following we present a number of contributions to the design of interaction mechanisms using mobile and wearable devices to enable more freely distant interactions with LHRD-based visualizations.



Figure 2.3.1: Multi-user CMV application on an interactive wall-sized display: (a) Interaction from close (touch) and distance (mobile device); (b) Data selection; (c) Details on demand; (d) Interactive ruler for value comparison; and (e) Magic lens with menu. Source: Langner et al. (2018).

2.3.2 Interaction via Handheld Devices

Hereafter, we focus on mechanisms that enable distant interaction with large displays (i.e. interacting without touching the display) mediated through mobile and wearable devices. The goal is to understand whether and how one could leverage these devices to improve visual data exploration on large or wall-sized displays.

Kister et al. (2017) proposed a set of techniques to support interaction with graph visualizations using mobile devices as a prop, which serve both as an additional visualization display and as a pointing device to interact with the LHRD. The interaction mechanisms cover different types of tasks (e.g., selection, details-on-demand, and filtering), and can be performed from close proximity to the display and remotely from afar. They are defined as follows:

- the *selection techniques and details on demand* include
 - tapping a node on the large display opens associated details on the mobile (Figure 2.3.2a1);
 - encircling multiple nodes enables group selections (Figure 2.3.2a2);
 - physically manipulating the mobile device for remotely pointing to an area in the visualization provides a focus view on the mobile (Figure 2.3.2a3); and



Figure 2.3.2: Set of mobile-based interaction technique for LHRD-based graph visualizations. Source: Kister et al. (2017).

- the focus view can be used for remotely selecting nodes in the visualization using either tap or encircling selection techniques (Figure 2.3.2a4).
- the *adjacency matrix* consists of an alternative representation that can be extracted from the large display to the device and moved freely in space, which can also be used to modify the edges within the graph (Figure 2.3.2b);
- the *tangible graph lenses* allows to
 - bring neighbors by pulling in the adjacent nodes of all nodes in focus as the user moves the mobile in the space in front of the wall-sized display, which creates a local “friendship” overview of nodes (Figure 2.3.2c1); and
 - to enlarge nodes with specific attribute values (Figure 2.3.2c2).
- the body-relative attribute filtering support selection of individual attribute ranges via a left-right movement of the device, and to brings the selection into focus via a down movement (Figure 2.3.2d); and
- the *sieve filter tool* enable the user to compare nodes within a cluster based on attributes (e.g., age); it visualizes every node as an independent

object and, through a shake gesture, the user can virtually throw all elements in the previously defined filter barriers (Figure 2.3.2e).

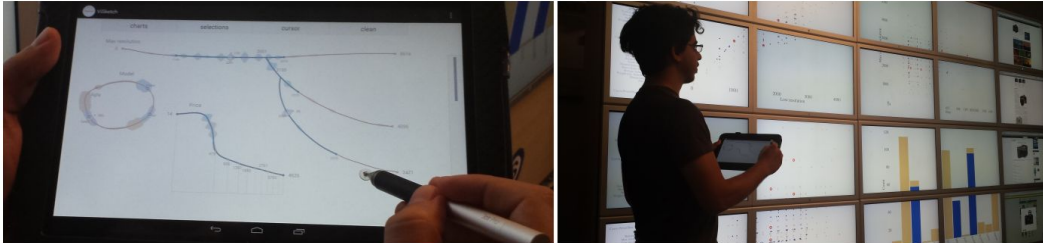


Figure 2.3.3: A mobile-based interaction technique to directly sketch visualization controllers. Source: [Tsandilas et al. \(2015\)](#).

The authors showed that when using the above interaction technique, users would either spread their attention between the wall-sized display and the mobile device or mostly focus on the mobile. In order to decouple control and visualization in a wall-sized display, [Tsandilas et al. \(2015\)](#) proposes a mobile sketching interface (Figure 2.3.3) that allows the users to draw controllers that best suit their needs instead of using a set of predefined widgets. A small combination of sketches and gestures enable users to create interactive components, such as slider branches and data transformation tools, to investigate detailed aspects and subsets of a dataset.

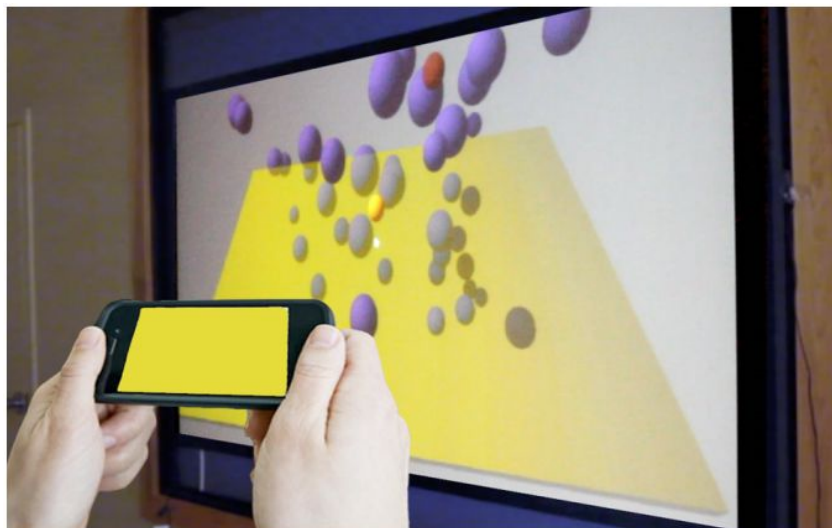


Figure 2.3.4: A technique that enables 3D interaction with nearby large displays by vertically swiping a mobile device. Source: [Pietroszek et al. \(2015\)](#).

The *Tiltcasting* technique enables 3D interaction with large displays via a smartphone (Pietroszek et al., 2015). The technique allows to scan the 3D space by vertically swiping the phone, which reveals occluded targets in the space (Figure 2.3.4). Then, users can interact with virtual objects through a 2D plane that correspond to a “cast” from their phone into the 3D space, which enables to select targets regardless of occlusion, and to easily judge the target depth. Along the same lines, Grandi et al. (2018) propose a collaborative interaction (i.e. two or more people interacting with the same virtual interface in order to achieve a common goal) technique leveraging a mobile device tangible and tactile input to translate, rotate and scale 3D objects in virtual environments.

Spindler et al. (2010) employ handheld tangible views, such as a piece of cardboard, as magnifying lenses that serve to augment the visualization on a large display with additional representations. Their findings showed that visual feedback helps users to mentally link local and global views; translation should be used for navigation within the presentation space; freezing is essential to temporarily decouple a tangible view from or multiple axes, which support comparison tasks; direct pointing is essential for interacting within local or global views.



Figure 2.3.5: Bar chart visualization fixed on the mobile device (left) and in space (right). Source: Büschel et al. (2016).

Handheld devices can serve as portals on a virtual data visualization (Pahud et al., 2018), which do not augment the existing display, but rather enable the viewer to interact with the virtual object. Using a similar approach where visualizations are fixed in space or on the device, Büschel et al. (2016) reported that simple navigation tasks benefit from spatial interaction for being free touch input, which latter could be used for other tasks, such as manipulating the visualization through widgets (Figure 2.3.5). Further, they observe that using a set of constrained gestures, the physical demand is lower when having

the data fixed on the device than on space. In a wider study using this same approach, users perceived spatial interaction as more supportive, comfortable and overall preferable to touch input (Büschel et al., 2017).

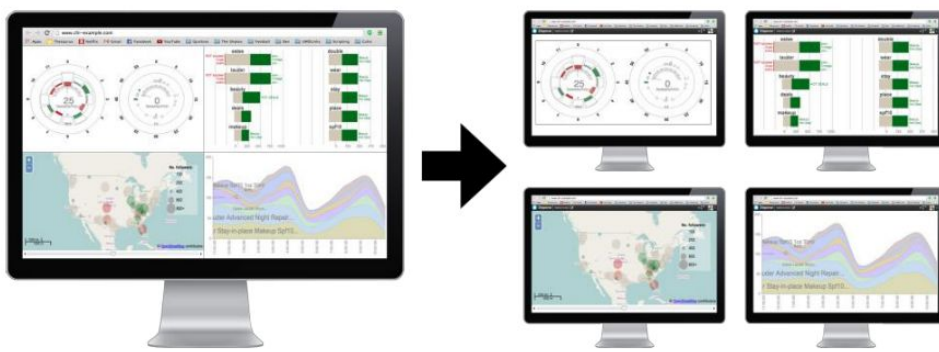
Although the extensive use of these devices can be tiring, the use of techniques such as *clutching* and *freezing* help to reduce the physical demand by allowing the user to lay down the device for a while. Furthermore, wearable devices (e.g., smartwatches, wristbands) could reduce tiredness caused by handheld devices and increase the user's concentration towards the visualization. The framework proposed by Horak et al. (2018) uses interaction mechanisms embedded in a smartwatch to explore data items, track interaction histories, and alter visualization configurations on a wall-sized display. User studies performed by the authors showed that the participants were focused on the large display while interacting eyes-free on the watch, which augments and mediates the functionalities by serving as a personalized toolbox. Eyes- and ears-free interaction is possible due to wearable devices triggering users' proprioception sense, which enables instantly invocation and dismissal of the device at any time for immediately switching between tasks, and intuitive interaction by using the same actions for input and output (e.g., clicking on a single button on the wristband) (Lopes et al., 2015).

2.3.3 Multiple Displays

Although physical navigation and interaction has shown benefits for exploring data on large high-resolution displays, while improving users' approach, perception and engagement with the visualization, such displays are still comparatively scarce to conventional ones. Therefore, alternative approaches have been proposed to leverage the convenience of ordinary displays, while increasing the visualization space. The Disperse framework proposed by Monroe and Dugan (2015) allows to split CMV applications across multiple screens and devices (i.e. displaying one view per screen or device) to enable more data-rich displays, provenance and both remote and co-located collaboration (Figure 2.3.6a).

Using mobile devices, Langner et al. (2017) proposes *VisTiles*, a framework that allows to organize visualizations by spatially co-locating mobile devices, which enables the user to construct and adapt their individual interface in terms of positioning visual components (Figure 2.3.6b). Each mobile device correspond to a *tile*, which role can be to display visual representations of

data, or to display menus or widgets that are used for additional functionalities (e.g., changing visualization parameters or dynamically querying data items). The approach leverage a physical workspace, which does not constrain the arrangement of views to a grid-based layout, but allow the user to freely position views wherever within the workspace, and the views become both physical and tangible. To address issues of limited screen space and visual clutter, they use a strategy of one visualization per device, requiring the use of several devices, which are not always available.



(a) The Disperse framework. Source: Monroe and Dugan (2015).



(b) The VisTiles framework. Source: Langner et al. (2017).

Figure 2.3.6: Visualization approaches to increase screen space through the distribution of views throughout multiple screens and/or devices.

To preserve the informative and usefulness aspects of a visualization when dispersing views across multiple heterogeneous devices, Horak et al. (2019) proposes the following heuristics:

- to closely place views with data degree and visual similarity or dependencies (e.g., a view that serve as input to others);
- to allocate space proportional to the number of data points the view encodes and keep uniform scaling to avoid tempering the original perception;
- to assign view according to device suitability; and
- if applicable, user preferences outweigh all other heuristics.

According to [Weiser \(1999\)](#), users can easily interact with multiple devices, perceiving them as components of the same underlying system instead of single entities. In this context, [Zagermann et al. \(2020\)](#) studied the influence of interaction techniques, device utilization, and task-specific activities on user performance within a multi-display system, which enables the use of multiple tablets to work with pieces of information by freely moving and arranging sticky notes on a single tablet or transferring them across multiple tablets. The authors showed that the interaction has little influence on completion time of tasks (i.e. explore, sort and distribute stick notes across tablets), and users prefer fast techniques even if they are not familiar with them. Furthermore, using many devices helped users to develop different problem-solving strategies, which authors suggest to be influenced by legacy bias (i.e. pre-existing knowledge with prior interfaces and technologies). The latter could be mitigated by guiding and training users on the purpose of each device within the multi-display system to solve a particular task.

2.3.4 Synthesis

In this thesis, we are dealing with large and multidimensional datasets to describe the urban mobility phenomenon via complementary objects of interest (trips and travel flows, the territory, and daily trajectories), which are themselves described over multiple spatio-temporal granularity levels and different thematic attributes. One of our goals consist on providing enough flexibility to allow the user to construct their visualization interface in meaningful ways according to the mobility indicators and data dimensions that are more suitable to the ongoing analysis. Assuming, for instance, that one may not need to explore the three objects simultaneously, or even focus on only some of the thematic attributes, when the goal of the analysis is to answer one or two specific questions underlying urban mobility.

In this context, we are particularly interested on using conventional displays instead of large, high resolution ones, since they are more accessible to our prospect users, i.e. urban planners and researchers on the field of urban mobility. Therefore, to provide flexibility and enough visualization space to explore the data, we opted for using multiple synchronized analytical displays, which amount and spatial position are chosen by the user. Thus, we believe that using mouse and keyboard-based techniques to interact with multiple synchronized displays could also be uncomfortable, since the user would stay quite close to the visualization, which could become large when more than two displays are involved and, as we have seen, this proximity may be prejudicial to user experience and performance. To provide a more comfortable and efficient interaction, we use the tactile and tangible input of a mobile device, i.e. a tablet. Particularly, the physical interaction supports the exploration of data over time, which intends to reduce some limitations of the time animation technique, such as color-blindness.

The idea implies on “scaling up” the visualization and adding non-conventional interaction methods to what is already a complex visual analytics approach due to the multidimensional aspect of the data and the analysis based on the exploration of three objects of interest. This approach could easily engender high cognitive load, which could negatively affect user performance and satisfaction. There are two ways to prevent this outcome: (1) wisely choosing which methods to include and how to combine them, and (2) to evaluate the approach with “real” users. In this spirit, the next section describes the existing user experiments protocols, the advantages and difficulties of applying them to assess the usability and suitability of visualizations.

2.4 User-based Evaluation of Visualizations

The thirty-five surveyed studies presented in section 2.2 provided some sort of validation of the proposed visualization, which was mostly done through case studies, where the visualization approach was applied to a real dataset. Fourteen authors could gather a small group of experts (i.e. 2 to 7 people), to whom they demonstrate the system’s interactive and visual encoding, and the case studies. The experts were then asked to provide feedback regarding the visual encoding and suitability of the visualization to explore the dataset. These feedback were mostly collected through informal interviews. Three publications reported formal experiments with a large sample of participants

(i.e. from 15 to 62 people) non-experts on the domain of application. These experiments were mostly interested on evaluating the graphics suitability to represent the data through factors such as user performance, system's usability, response accuracy and time. Further, some publications were focused on visualizing big data, where machine learning algorithms were employed for identifying mobility patterns. In these cases, the authors were also interested on evaluating the suitability of the data treating process through measures such as scalability and efficiency.

This pattern of evaluation absence is consistent to what has been observed by other authors, such as [Ellis and Dix \(2006\)](#) and [Andrews \(2006\)](#), who emphasized the lack of user-based evaluations and the weakness and strengths of the few performed in the field of information visualization. From the 65 papers reviewed by [Ellis and Dix \(2006\)](#), only 12 report any kind of user evaluation, and from these, only two studies were considered particularly useful. We notice that, although these studies date from 2006, the evoked issues are still topical, particularly the difficulty for recruiting real users and performing the "right tasks", considering the exploratory nature of visualizations.

According to [Knight \(2001\)](#), evaluating a visualization consists on considering the suitability of (1) the interface to support the tasks it was designed for, and (2) the representation and metaphor levels as to how well the graphics support the data. However, this process is not trivial because visualizations are often designed for more exploratory tasks, which are the hardest ones to replicate in an experiment. Furthermore, visualizations are generative artifacts, which means that they are not something of value by themselves, but only yield results in some context ([Ellis and Dix, 2006](#)), i.e. a thematic domain of application. Therefore, one should have professionals on that domain using the tool to observe its added value. However, these people are difficult to recruit because they are not necessarily available to take part in the experiments and specially not to participate in long-term studies, which are the best method to thoroughly evaluate an information visualization interface while refining and understanding general principles or guidelines for designing such tools, and allowing expert users to achieve their goals ([Shneiderman and Plaisant, 2006](#)).

In this spirit, a user-based evaluation is certainly the most suitable approach to assess usability and usefulness of visualizations, since they involve the people for whom the system is intended: the users. Usability measure the tool's ability to meet user performance and satisfaction objectives, and is conducted based on a number of representative user tasks, for which usability

factors are measured (Koua and Kraak, 2004). Usefulness is the quality of having utility, and specially practical worth and applicability, which can only be measured by the end-user, who is intended to use the tool in their daily work routine. These aspects are typically measured through three main kinds of testing methods (Andrews, 2006), defined as follows:

- the *formative test* consists on observing a small number (3 – 5) test users using the interface in order to gain insight into which problems occur and *why* they occur, which distinguishes this testing method from others. It follows a classical design of *thinking aloud*, which provide valuable feedback for improving design and fixing bugs. However, they are rarely generalizable to other information visualization tools because of the small number of test users, which is usually too small to be considered a representative sample, and evidence shows that users who are thinking aloud both change their behavior and are slower than users who do not think aloud (Ericsson and Simon, 1984, pg. 105).
- the *summative test* consists on collecting bottom-line measurement data, such as task completion time or number of clicks, through a *formal experiment*, which are mainly applied for comparing two or more information visualization interfaces. There are typically three experimental designs that can be followed to allocate test users to different conditions:
 1. *Independent / unpaired measures / between-groups*, which uses different participants in each conditions of the independent variable
 2. *Repeated / paired measures / within-groups*, which uses participants in each condition of the independent variable
 3. *Matched pairs*, which uses different participants in each condition, but they are matched in terms of important characteristics (e.g., gender, age, education level, etc.)

Statistical significance is rarely found with less than 10 test users, which make the second design tempting, since significant differences could be found with fewer users. Further, the design allow to “re-use” the same participants for each interface, eliminating any effect of individual difference between users, which could also be mitigated via the matched pairs design.

- the *usage studies* involve observation and/or recording of users over a long period of time working on an interface. Many usage studies rely on self-reporting data (i.e. users keep a diary of what they did), which

accuracy could be arguable. The alternative consists of recording and manually describing user events, which is extremely time-consuming (i.e. for each hour of video, around ten hours are spent manually coding user events). Although they are well-suited for learning how users use a piece of software, they are not useful for objective comparison of two or more interfaces.

Formal experiments are the most reliable testing method for evaluating an information visualization and generalizing the outcomes, since it compares the interface under evaluation with traditional interfaces and engages enough test users to ensure statistical significance. However, according to [Andrews \(2006\)](#), it would be unfair to compare novel visualization tools, often buggy and incomplete (i.e. prototypes), to tested traditional interfaces. Further, even after extended training of test users with the new interface, it is extremely difficult to overcome the bias caused by familiarity with the traditional ones.

Typically, formal experiments test simple locate, count and compare tasks, which are well-adapted to evaluate specific aspects of a visualization, such as color-code interpretation, and to detect problems. Furthermore, researchers often choose tasks (and datasets) that suit a novel technique. However, the real benefit from information visualization systems comes from a deeper insight gained from much more exploratory tasks ([Andrews, 2006](#), [Ellis and Dix, 2006](#)).

Moreover, the specific objective for which it was developed might make the interface “incomparable” in terms of the domain questions it aim to answer and the kind of data being explored, for instance. One would have to find a visualization designed for the exactly same purpose, and considering the same power of analysis (i.e. the extent to what the represented data enable the answering of thematic questions) that the novel tool intends to provide. This issue combined with the difficulty to find real users might be probably what cause many authors to validate their approaches only via case studies. Nonetheless, [Ellis and Dix \(2006\)](#) states that although one cannot really evaluate a visualization, empirical evaluations complemented with reasoned justification can lead to reliable and strong validation of the visualization. These justification elements could be arguments based on existing published results of experiments and analysis, our own empirical data, and expert’s opinion.

2.5 Summary

In this chapter, we presented an extensive literature review of VASs conceived to support the analysis of urban mobility data. These visualization interfaces are classified according to the object of interest supported by the visual analysis. We could notice that no existing visual analytical interface enable an analysis of urban mobility data through indicators that describe the three objects of interest over multiple spatio-temporal granularity levels and thematic attributes. Two solutions cover those objects of interest at some level, but the variety of thematic information is quite limited and they are totally based on 3D visualizations, which are still limited by 2D-based interaction. Furthermore, we presented a brief overview regarding non-conventional displays and interaction techniques that could improve the visual exploration of large and multivariate datasets, and user evaluation methods that could be used to assess the usability and suitability of a visualization interface, while also pointing out the advantages and difficulties of such evaluation processes. The content of this chapter should be sufficient to guide the reader throughout the remaining of this thesis, which present (1) our visualization framework and (2) the incremental methodology based on user evaluations we followed during the conception and implementation of the referred framework.

The eSTIME Framework

3.1 Introduction

In the last decades, many in-depth studies have been carried out in social sciences and various other related disciplines for understanding the numerous aspects of human migration and their impacts on social, economic and cultural changes (Montanari, 2002). In this work, we are particularly interested in the aspects of daily human migration within an urban area in order to address three categories of questions that are of great concern within the fields of geography and urban planning, defined as follows:

1. Which are the daily traveling patterns of a population? Which are the resulting processes of exchanges between places within an urban area?
2. How the presence of people varies over time throughout the different places within an urban area? How the activities and socioeconomic and demographic profiles of individuals determine the usage of these places?
3. How individuals schedule their activities and trips over time according to a particular spatial context?

The eSTIME framework addresses these questions by exploring the variation over space, time and thematic attributes of three complementary objects of interest extracted from urban mobility data:

1. the *travel flows and trips*, which exploration helps to describe the traveling patterns of a population. Travel flows reveal the urban structure through the aggregation of trips between origin and destination (O/D)

- locations. Further, we derive the trips amounts per individual and aggregate over the whole population, the modalities per trip purposes and transportation modes, and the trips variation over different socioeconomic and demographic aspects of individuals or land types.
2. the *territory*, which exploration helps to understand the usage patterns of different places within the urban area according to the demographic and socioeconomic aspects of the people that visit each place and the types of activities they perform there. Thus, we estimate the presence of people at each place and its variation at different times of the day.
 3. the *daily trajectories*, which are defined as a space-time path described by the activities one performed over time in the visited places and the transportation modes one used to travel from one place to another. These trajectories are used to set up typologies that describe the diversity of activity schedules that underlay and explain the need of traveling (Robette, 2011).

The analysis of daily urban mobility through the eSTIME framework follows a four-step workflow (Figure 3.1.1), which is thoroughly presented in this chapter. The *data preparation* stage consists on structuring the input dataset (see Section 3.2) in order to extract information matrices of flows, presence, and activity sequences. These matrices allow us to derive *statistical indicators and a typology* (see Section 3.3) from the aforementioned objects of interest, which together describe the daily urban mobility phenomenon. We derive statistical indicators of travel flows, variation of mobility and presence of people per transportation mode and trip purpose over multiple spatio-temporal granularity levels, and a typology that group together daily trajectories according to the similarity of their embedded activity programs. The whole process of structuring data and deriving indicators was performed using the R statistical and graphical environment (R Development Core Team et al., 2011).

The *querying* stage consists on establishing a system of tasks (see Section 3.4) that allows the user to query the mobility indicators from different spatio-temporal granularity levels (i.e. multiple spatial or time partitioning) and thematic attributes (i.e. transportation modes, trip purposes and activities), and objects. The latter corresponds to a group of individuals belonging to a particular cluster of the typology. Finally, the *interactive visualization* comprises the eSTIME interface (see Section 3.5), which support the visual representation of indicators through a set of charts and maps, which tactile

and tangible interaction allows one to query the displayed indicators through our system of tasks.

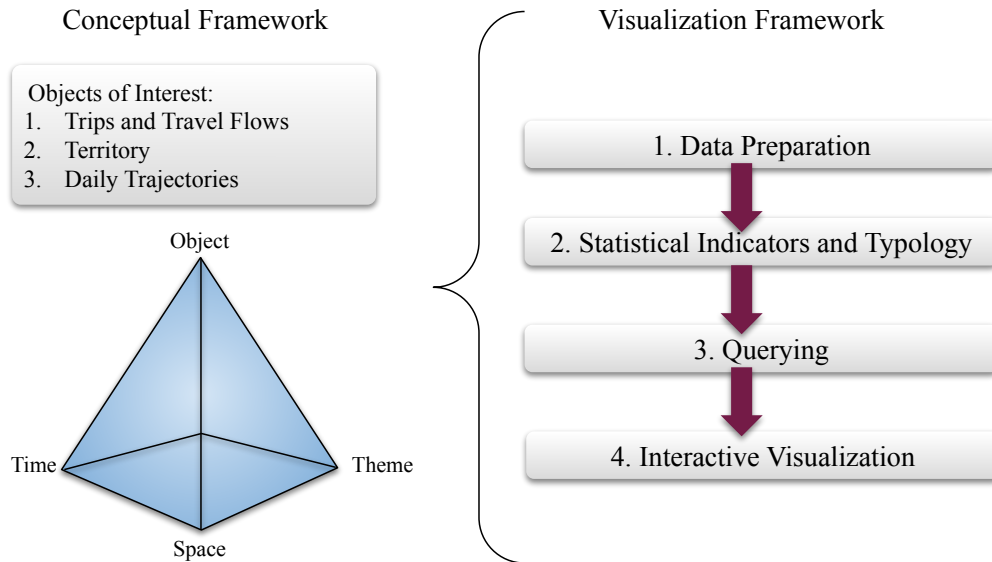


Figure 3.1.1: The eSTIME Framework supports the analysis of daily urban mobility on the basis of three complementary objects of interest explored through a four-step workflow. The (1) *data preparation* phase structures the input data and extracts information matrices, which are afterwards used for (2) deriving a *typology of activity sequences* and *statistical indicators* to describe daily urban mobility. The (3) *querying* stage establishes a system of queries to explore indicators over space, time, objects and attributes. Finally, the *interactive visualization* proposes visual and interaction tools to explore the data through our indicators and system of tasks.

3.2 Data Preparation

Typically, movement data contain items called *position records*, which specify the geographical position of some entity at a particular time moment (Andrienko and Andrienko, 2010). The data can be either continuous, i.e. defined by a sequence of geographical coordinates x, y separated by short timestamps (e.g., GPS-based data) or discrete, i.e. defined by origin end destination positions in space, which may be sparsely disposed throughout the time period under observation (e.g., survey-based data). The data is often enriched with

semantic information describing the trips and/or entities in terms of trip purposes, transportation modes, activities and socio-demographic aspects.

Daily urban mobility patterns can be described through a spatio-temporal dataset detailing individual's movements within a urban area during a time interval of 24 hours. The data has three fundamental sets: space (*where*) defined by a set of locations S , time (*when*) defined by a set of time units T , and objects O (*what*) defined as physical and abstract entities. [Andrienko et al. \(2011\)](#) classify objects into five categories according to their spatial and temporal properties:

- a *spatial object* is an object having a particular position in space at any time of its existence;
- a *temporal object*, or *event*, is an object having limited time of existence with respect to the time period under observation;
- *spatial events* are objects having particular positions in space and time;
- a *moving object*, or *mover*, is a spatial object capable of changing their spatial positions over time; and
- *moving events* are events that can change their spatial positions over time (e.g., an hurricane).

In this work, we are particularly interested in *movers* and *spatial events*, which are jointly called *spatio-temporal objects*. A *spatial event* is defined as the pair (t, s) , $t \in T$, $s \in S$, where s corresponds to a particular position in space and t to a position in time, which defines a change on the spatial position of a mover. The set of spatial events triggered by a mover results on a *trajectory*, which is itself a spatial object whose position in space is the set of places visited by the mover. Thus, a trajectory is defined as a complex spatial event that can be segmented into a set of elementary spatial events, i.e. *moves* and *stops*. [Baglioni et al. \(2008\)](#) define *stop* as a time interval when the mover was present in a spatial location carrying out a particular activity, and *move* as a spatio-temporal line between two locations representing either two consecutive stops or a trajectory start or end.

Furthermore, the elements of each set have properties represented by a set of attributes A , which values can be elements of T , S , or O (e.g., a movement's duration and distance), more complex constructs involving elements of

T , S , or O (e.g., speed), or *thematic attributes*, which do not involve space or time (e.g., activity, transportation mode, and socio-demographic characteristics). Particularly, our visualization framework addresses the latter type of attributes, which input data should ideally provide (or allow the derivation of it) in order to analyze urban mobility through our visualization framework. Henceforth, we present the structure of the original dataset used as input in our analysis workflow and the transformation process we applied to the data in order to obtain information matrices of flows, presence and sequences of activities which are the basis for deriving mobility indicators.

3.2.1 Original Dataset

Since 1976, the French ministry of transportation proposed a detailed methodology for conducting surveys on the daily mobility of inhabitants of an area: the Household Travel Surveys (*Enquête Ménage Déplacements* in French). These are today standardized by Cerema (acronym for *Centre d'études et d'expertise sur les risques, l'environnement, la mobilité et l'aménagement* in French), which is a public institution focused on supporting public policies placed under the dual supervision of the ministry of ecological transition and the ministry of territorial cohesion and relations with local authorities¹. Further to the conventional HTS, which is applied to urban areas, a Medium-sized Town Travel Survey (MTTS, *Enquête Déplacements Villes Moyennes* in French) and a Large Area Travel Survey (LATS, *Enquête Déplacements Grand Territoire* in French) are available for surveying medium-sized towns and large areas, respectively (Richard and Rabaud, 2018).

These surveys typically interview 1 to 2 percent of the resident population randomly selected from fiscal databases with geographic stratification and represent currently the main reference for local mobility knowledge in France, being used for preparing and assess development and urban transportation policies, and for travel modeling (Richard and Rabaud, 2018). The territory is geographically divided into polling sectors, which are compatible with the IRIS2000² territorial partition from INSEE³. To ensure statistical significance, at least 20 polling districts must be defined, and at least 70 households and

¹<https://www.cerema.fr>

²A system for dividing the country into units of equal size, known as IRIS2000. In French, IRIS is an acronym of 'aggregated units for statistical information', and the 2000 refers to the target size of 2000 residents per basic unit.

³*Institut National de la Statistique et des Etudes Economiques* (<https://www.insee.fr>)

160 persons must be interviewed in each one, totaling a minimum of 1,500 households interviewed over the territory (Certu, 2013). Then, to represent the real size of the area's population, the sample is adjusted via coefficients defined on the basis of place of residence, household size and automobile ownership.

In this work, we recovered data from an HTS applied on the urban area of Grenoble metropolis (CEREMA, 2010), and from two LATs applied on the metropolitan areas of Lyon (CEREMA, 2015) and Rennes (CEREMA, 2017) (see Table 3.2.1 for sampling details). Recruitment and interviews are performed face-to-face (FTF) in the respondents' place of residence in the case of HTS and densely populated LATS areas, and by telephone in the case of MTTs and the rest of LATS area (Richard and Rabaud, 2018). The resulting dataset describe the mobility of every household member aged five and older during the 24 hours of a weekday, from 4am (the day before) to 4am (the survey day). The survey also gathers socio-demographic information about the interviewed person and household (Richard and Rabaud, 2018). The data records are arranged as rows in five tables describing the following components:

- the interviewed *households*, which table contains the weekday when the reported trips took part, household size (i.e. number of residents), residence type (e.g., individual house, building), the type of occupancy (e.g., owner, tenant), code of commune where the household is located, ownership and type of vehicle, parking place during day and night, possession of internet connection, type of household (i.e. ordinary or student), and an adjustment factor based on the place of residence, the household size and automobile ownership;
- the interviewed *people*, which table contains information describing the household to which they belong, their gender, age, working status and schedule, whether the latter is free or imposed, socioprofessional category⁴, education level, possession of mobile phone, e-mail, driving license, subscription to the public transportation system, and their use frequency of various transportation modes (e.g., automobile, bicycle, public transportation);
- the *trips* of each person, which table contains information that describe the person to which the trip belongs, the departure and arrival hours and

⁴The Classification of Professions and Socioprofessional Categories, or PCS, classifies the population by a combination of profession (or former profession), hierarchical position and status (salaried employee or otherwise) (see <https://www.insee.fr/en/metadonnees/definition/c1493>)

minutes, origin and destination (O/D) locations, activity performed at the origin and destination, duration, number of mechanical transportation modes used, traveled distance, and distance as the crow flies (both in meters);

- the *rides* of each trip, which table contains information that describe the trip to which the ride belongs, the walking time to the location where the ride begins and after it finishes, the transportation mode, the O/D locations, type and place of parking, traveled distance and distance as the crow flies (in meters); and
- the *opinion* of interviewed people regarding life quality in the urban area (e.g., security, education, leisure, environment, employment opportunities), the urban travel conditions (e.g., accidents risks, traffic noise, public transportation, pollution, parking), transportation modes rating, among other aspects that may vary across territories.

<i>Aspect</i>	<i>HTS Grenoble</i>	<i>LATS Lyon</i>	<i>LATS Rennes</i>	
Year	2010	2015	2018	
Interview method	FTF	FTF and telephone	FTF and telephone	
Number of Cities	354	446	392	
Number of Households	7,600	16,361	7,981	
People	Interviewed	16,641	28,230	11,000
	Representing ⁱ	800,000	2,292,000	1,000,000
Trips	Counting	63,336	99,585	44,000
	Representing	2,900,000	6,006,000	4,000,000

ⁱ The number of people and trips represented by the data is estimated through adjustment factors based on the place of residence, the household size and automobile ownership.

Table 3.2.1: Summary of the datasets' sample for Grenoble, Lyon and Rennes metropolitan areas.

The temporal information describing departure and arrival time is subjectively reported by the interviewed person in hours and minutes, which precision may vary according to the person's memory of the event. In order to define time as a continuous variable, the dataset present time from 4 to 28 hours, where the values from 24 to 28 stand for the night hours from midnight to 4am.

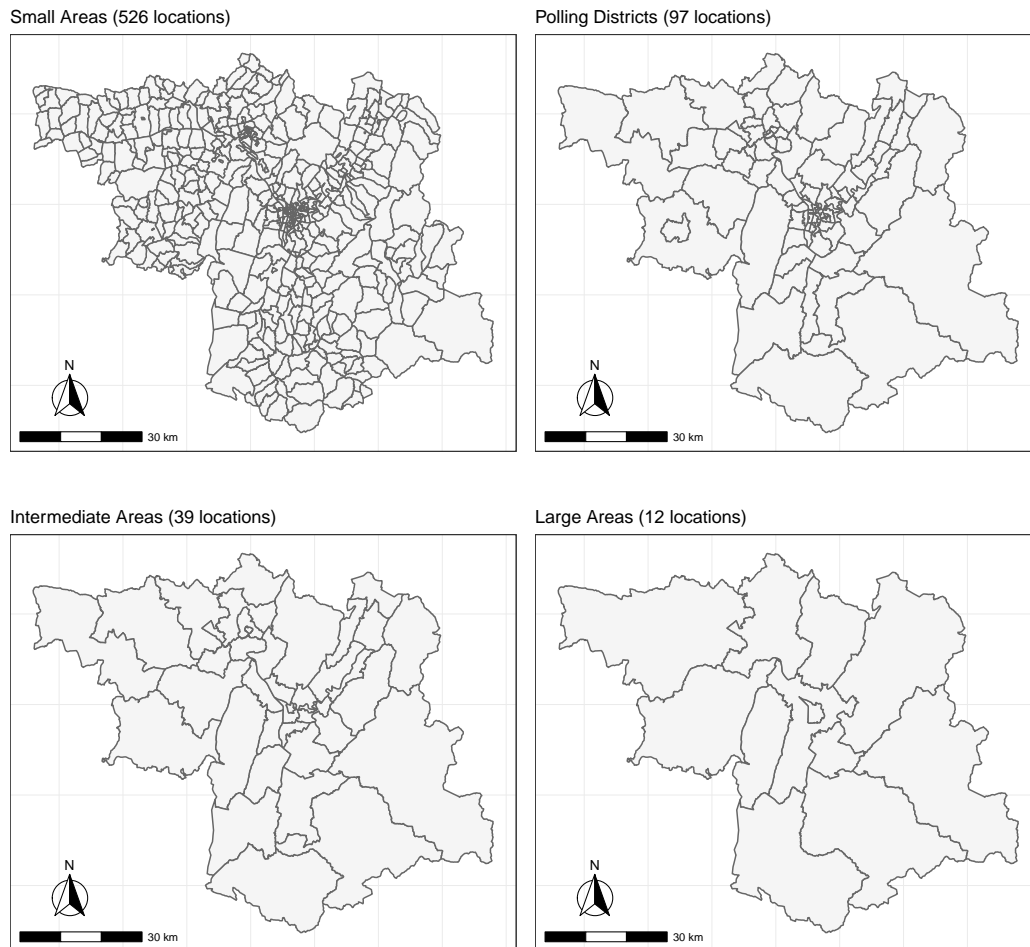


Figure 3.2.1: The territorial partitions of the great region of Grenoble metropolitan area.

The O/D *locations* are predefined districts in the survey, which surface varies according to the spatial granularity. For each area, the survey provides four territorial partitions with increasing coarse granularity (exemplified in Figure 3.2.1 and summarized in Table 3.2.2), which locations in each partition correspond to a grouping of locations existing in the finer territorial partitions. They are defined as it follows:

- a set of *small areas*, a fine-grained territorial partition used to help the interviewed people to describe their trips during the survey application;
- a set of *polling districts*, which are the primary sampling units to disseminate the survey's results, in which a number x (roughly the same

Region	Small areas	Polling districts	Intermediate areas	Large areas
Grenoble	526	97	39	12
Lyon	1,191	169	58	11
Rennes ⁱ	570	83	-	-

ⁱ At the time of this thesis, the data for the region of Rennes was only available for small areas and polling districts.

Table 3.2.2: Number of locations per territorial partition within each dataset.

for every district) of people was interviewed. The polling districts' size varies according to the population density: they are smaller in the urban centre, corresponding to large neighborhoods, and larger in the suburban areas, corresponding to a group of municipalities;

- a set of *intermediate areas*, which reconstitute the department council⁵ areas within the region of Grenoble, and represent the inter-municipalities or neighborhood groups of Lyon; and
- a set of *large areas*, which represents the inter-municipalities within the region of Grenoble, and reconstitute the SCOT (*Schéma de Cohérence Territoriale*)⁶ areas of Lyon's agglomeration.

The interviewed people can describe their trips according to a detailed list of around thirty types of trip purposes and twenty types of transportation modes, which elements may vary according to the available transportation or possible activities in the surveyed area.

⁵The department councils of France are representative assemblies elected by universal suffrage in 98 of the country's 101 departments. A description of department councils areas of *Isère* can be found in <https://www.data.gouv.fr/fr/datasets/territoires-du-conseil-departemental-isere/>.

⁶The *Schéma de Cohérence Territoriale* is a French urban planning document which determines a territorial project aiming to align the municipalities' policies, specially with regard to housing, mobility, commercial development, the environment and landscape. The description of Lyon's SCOT areas can be found in <https://www.scot-agglolyon.fr/>.

3.2.2 Information Matrices

The input dataset underwent a transformation procedure that consists on establishing the spatial and temporal granularity levels and thematic attributes from which we deduce the information matrices that serve as basis for the derivation of the typology of activity programs and the statistical indicators from flows, trips, and territory describing the daily urban mobility phenomenon.

We set the spatial granularity level as the four territorial partitions originally provided in the dataset, and the temporal dimension is discretized into two sets of time intervals with increasing fine granularity:

- a set of *one-hour intervals* from 4 to 28 resulting in a set of twenty-four time units, which we use to obtain information matrices of flows and presence; and
- a set of *5-minutes intervals* from 240 to 1680 resulting in a set of 588 time units, which is used to produce the table of activity sequences, enabling a higher precision to identify the changes of activity within sequences.

We kept the time range from 4 to 28 hours to avoid invalid situations where activities start before midnight and finish during the night, in which case a range with time resetting at midnight would result in an end time that is before the starting time. However, we will visually represent such information through a time range resetting at midnight for the sake of consistency with the real-life time. We address three kinds of thematic attributes, defined as follows:

- the *trip purposes* are grouped into seven categories:
 - *home*, which comprises trips destined to one's place of residence, either primary or secondary one (e.g., occasional residence or hotel);
 - *leisure*, which comprises mainly sports, promenades, eating out, and window-shopping;
 - *shopping*, which comprises trips to the shops and supermarkets;
 - *education*, which describes trips destined to a school or college;

- *business*, which describes trips destined to one’s workplace;
 - *personal business*, which includes visits to services, medical consultations, job searching, and so on; and
 - *escort trips*, which comprises trips with the purpose to accompany someone else (e.g., taking a child to school is escort education).
- the *transportation modes* are grouped into five categories:
 - *walking*, which does not include the displacements between home and a motorized transport;
 - *cycling*, either as a driver or a passenger;
 - *car/van*, either as a driver or a passenger;
 - *public transport*, which includes bus, metro, train, taxi, and other vehicles within the public transportation system; and
 - *other modes*, which include motorcycles, trucks (professional drivers), plane, wheelchair, agricultural vehicle, scooter, and so on.
 - the *socio-demographic aspects* describe individuals according to their
 - *gender*, which indicates whether the individual is male or female;
 - *age*, which we aggregate into six ranges: 5-17, 18-24, 25-34, 35-49, 50-64 and 65+ years of age;
 - *occupation*, which includes full-time employment, part-time employment, internship, university student, school student, unemployed, retired, and stay at home;
 - *professional category*, which includes business owners and shop keepers, executive and professionals, technicians and associate professionals, employees, blue collar workers, and no professional activity; and
 - *frequency of mode use*, which measures the frequency with which the individuals use each transportation mode in terms of several days per week, several days per month, rarely or never.

As we mentioned earlier, the data describes moves between O/D locations. However, for studying the presence dynamics of a population, we must know where each individual is located at different time intervals. Therefore, we transformed the trips table to extract the *stops* in between moves. Firstly, the tables of trips and rides were combined to associate the transportation

mode of each trip (Figure 3.2.2 – left); trips with multiple rides performed with different transportation modes are identified as *intermodals*. Secondly, we extracted the stop from each trip (Figure 3.2.2 – right), which corresponds to the time spent at the trip’s destination, which is itself the origin location of the next trip. The activity performed while in the stop is determined by the activity associated to the origin location of the trip, and the stop’s duration corresponds to the time difference between the arrival time of this trip and the departure time of the next one.

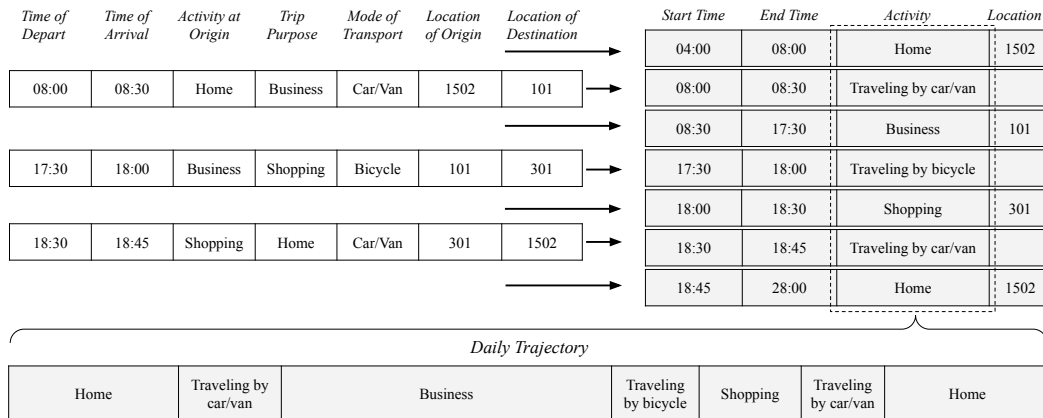


Figure 3.2.2: The data is organized into trips with depart and arrival times, trip purpose, transportation mode, and O/D locations (left), from which we derive the stops and moves (right). Adapted from: [Cochey and Tabaka \(2007\)](#).

Further, since we are interested on the daily activity schedule of individuals, we sequenced stops and moves to form *daily trajectories*, where stops are characterized by a location and an activity, and moves are described by the transportation mode used for traveling from one place to another (Figure 3.2.2 – bottom). The trajectories have a total duration of 24 hours, which arise out of summing up the duration of each stop and move.

Figure 3.2.3 presents the resulting structure of the dataset. Space and time exist independently of objects and are characterized by a size, which corresponds to the number of spatial locations and time intervals, respectively. Space is composed of spatial locations, which are described by a name, a geographical area (i.e. a polygon), latitude and longitude (i.e. the center of the area) and a surface measured in square kilometers. Time is composed of time intervals, which are described by a duration, starting and ending hours and minutes. Both time intervals and spatial locations characteristics change according to the granularity level.

A mover is characterized by an identifier (i.e. based on the polling district, place of residence, sample and person number according to their household) and the aforementioned socio-demographic information, and it is associated to only one daily trajectory. The latter is characterized by an identifier and is composed of stops and moves, which are defined according to space, time and thematic attributes. Both stops and moves contain a time interval describing their duration, start and end times. Each stop is characterized by an activity and is associated to a location that describes where it took place, while a move is characterized by a transportation mode and a trip purpose, and is associated to two locations, which describe its origin and destination.

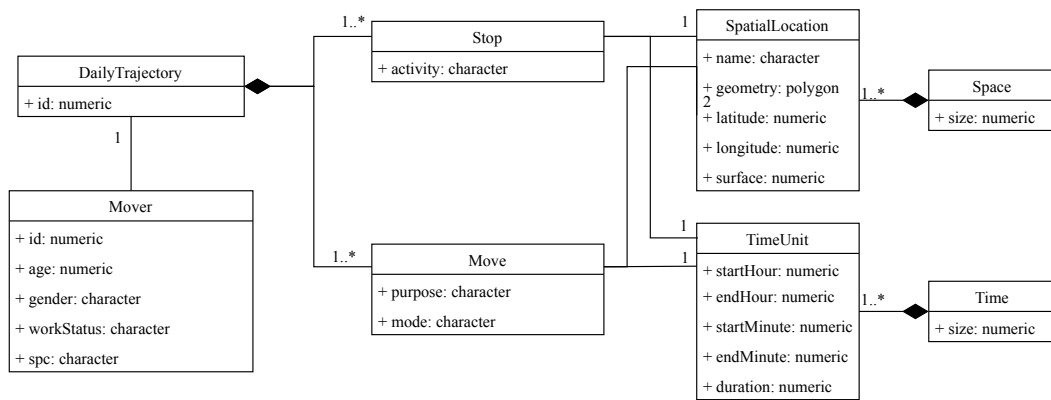


Figure 3.2.3: Components and relationship among entities of human mobility data.

This data structure allowed us to generate the information matrices for each spatio-temporal granularity levels and thematic attributes, as follows:

- *Flows matrix:* For each time unit $t \in T$ and trip attribute $a \in A$ (i.e. trip purpose or transportation mode), we generate a data table where each row represents a flow in the dataset, and columns represent origin and destination locations, and flow magnitude between them. Using the *Flows* package (Giraud and Beauguitte, 2016), we transform this data table into a matrix, which rows and columns correspond to the origin (i) and destination (j) locations, and the value in each position (i, j) of the matrix corresponds to the flow magnitude between these locations (Figure 3.2.4a);
- *Presence matrix:* For each activity $a \in A$ and for all activities taken together, we count the number of movers visiting each spatial location $s \in S$ at each time unit $t \in T$. This process results on a matrix of

presence per activity (Figure 3.2.4b), where rows i correspond to spatial locations and columns j to time units, and the value of each position (i, j) correspond to the number of visitors in the location at that particular time unit; and

<p>a)</p> <table style="border-collapse: collapse; margin-left: auto; margin-right: auto;"> <tr> <td colspan="2"></td> <th colspan="3" style="text-align: center;"><i>Destinations</i></th> </tr> <tr> <td colspan="2"></td> <th style="border-right: 1px solid black;">A</th> <th style="border-right: 1px solid black;">B</th> <th>C</th> </tr> <tr> <th rowspan="3" style="border-right: 1px solid black; vertical-align: middle;"><i>Origins</i></th> <th style="border-right: 1px solid black;">A</th> <td style="border-right: 1px solid black;">10</td> <td style="border-right: 1px solid black;">15</td> <td>0</td> </tr> <tr> <th style="border-right: 1px solid black;">B</th> <td style="border-right: 1px solid black;">0</td> <td style="border-right: 1px solid black;">20</td> <td>15</td> </tr> <tr> <th style="border-right: 1px solid black;">C</th> <td style="border-right: 1px solid black;">20</td> <td style="border-right: 1px solid black;">0</td> <td>5</td> </tr> </table>			<i>Destinations</i>					A	B	C	<i>Origins</i>	A	10	15	0	B	0	20	15	C	20	0	5	<p>b)</p> <table style="border-collapse: collapse; margin-left: auto; margin-right: auto;"> <tr> <td colspan="2"></td> <th colspan="6" style="text-align: center;"><i>Time units</i></th> </tr> <tr> <td colspan="2"></td> <th style="border-right: 1px solid black;">4</th> <th style="border-right: 1px solid black;">5</th> <th style="border-right: 1px solid black;">6</th> <th style="border-right: 1px solid black;">...</th> <th style="border-right: 1px solid black;">27</th> <th>28</th> </tr> <tr> <th rowspan="3" style="border-right: 1px solid black; vertical-align: middle;"><i>Spatial locations</i></th> <th style="border-right: 1px solid black;">A</th> <td style="border-right: 1px solid black;">10</td> <td style="border-right: 1px solid black;">15</td> <td style="border-right: 1px solid black;">20</td> <td style="border-right: 1px solid black;">...</td> <td style="border-right: 1px solid black;">15</td> <td>10</td> </tr> <tr> <th style="border-right: 1px solid black;">B</th> <td style="border-right: 1px solid black;">15</td> <td style="border-right: 1px solid black;">20</td> <td style="border-right: 1px solid black;">30</td> <td style="border-right: 1px solid black;">...</td> <td style="border-right: 1px solid black;">20</td> <td>10</td> </tr> <tr> <th style="border-right: 1px solid black;">C</th> <td style="border-right: 1px solid black;">10</td> <td style="border-right: 1px solid black;">25</td> <td style="border-right: 1px solid black;">35</td> <td style="border-right: 1px solid black;">..</td> <td style="border-right: 1px solid black;">15</td> <td>5</td> </tr> </table>			<i>Time units</i>								4	5	6	...	27	28	<i>Spatial locations</i>	A	10	15	20	...	15	10	B	15	20	30	...	20	10	C	10	25	35	..	15	5																																																																								
		<i>Destinations</i>																																																																																																																																				
		A	B	C																																																																																																																																		
<i>Origins</i>	A	10	15	0																																																																																																																																		
	B	0	20	15																																																																																																																																		
	C	20	0	5																																																																																																																																		
		<i>Time units</i>																																																																																																																																				
		4	5	6	...	27	28																																																																																																																															
<i>Spatial locations</i>	A	10	15	20	...	15	10																																																																																																																															
	B	15	20	30	...	20	10																																																																																																																															
	C	10	25	35	..	15	5																																																																																																																															
<p>c)</p> <table style="border-collapse: collapse; margin-left: auto; margin-right: auto;"> <thead> <tr> <th style="border-right: 1px solid black;"><i>Id</i></th> <th style="border-right: 1px solid black;"><i>Start Time</i></th> <th style="border-right: 1px solid black;"><i>End Time</i></th> <th colspan="3" style="border-bottom: 1px solid black;"><i>State</i></th> </tr> </thead> <tbody> <tr><td style="border-right: 1px solid black;">1</td><td style="border-right: 1px solid black;">240</td><td style="border-right: 1px solid black;">480</td><td colspan="3">H (<i>home</i>)</td></tr> <tr><td style="border-right: 1px solid black;">1</td><td style="border-right: 1px solid black;">480</td><td style="border-right: 1px solid black;">510</td><td colspan="3">T (<i>traveling</i>)</td></tr> <tr><td style="border-right: 1px solid black;">1</td><td style="border-right: 1px solid black;">510</td><td style="border-right: 1px solid black;">1050</td><td colspan="3">B (<i>business</i>)</td></tr> <tr><td style="border-right: 1px solid black;">1</td><td style="border-right: 1px solid black;">1050</td><td style="border-right: 1px solid black;">1080</td><td colspan="3">T (<i>traveling</i>)</td></tr> <tr><td style="border-right: 1px solid black;">1</td><td style="border-right: 1px solid black;">1080</td><td style="border-right: 1px solid black;">1110</td><td colspan="3">S (<i>shopping</i>)</td></tr> <tr><td style="border-right: 1px solid black;">1</td><td style="border-right: 1px solid black;">1110</td><td style="border-right: 1px solid black;">1125</td><td colspan="3">T (<i>traveling</i>)</td></tr> <tr><td style="border-right: 1px solid black;">1</td><td style="border-right: 1px solid black;">1125</td><td style="border-right: 1px solid black;">1680</td><td colspan="3">H (<i>home</i>)</td></tr> <tr><td style="border-right: 1px solid black;">2</td><td style="border-right: 1px solid black;">240</td><td style="border-right: 1px solid black;">540</td><td colspan="3">H (<i>home</i>)</td></tr> <tr><td style="border-right: 1px solid black;">2</td><td style="border-right: 1px solid black;">540</td><td style="border-right: 1px solid black;">570</td><td colspan="3">T (<i>traveling</i>)</td></tr> <tr><td style="border-right: 1px solid black;">2</td><td style="border-right: 1px solid black;">570</td><td style="border-right: 1px solid black;">1080</td><td colspan="3">B (<i>business</i>)</td></tr> <tr><td style="border-right: 1px solid black;">2</td><td style="border-right: 1px solid black;">1080</td><td style="border-right: 1px solid black;">1110</td><td colspan="3">T (<i>traveling</i>)</td></tr> <tr><td style="border-right: 1px solid black;">2</td><td style="border-right: 1px solid black;">1110</td><td style="border-right: 1px solid black;">1680</td><td colspan="3">H (<i>home</i>)</td></tr> </tbody> </table>	<i>Id</i>	<i>Start Time</i>	<i>End Time</i>	<i>State</i>			1	240	480	H (<i>home</i>)			1	480	510	T (<i>traveling</i>)			1	510	1050	B (<i>business</i>)			1	1050	1080	T (<i>traveling</i>)			1	1080	1110	S (<i>shopping</i>)			1	1110	1125	T (<i>traveling</i>)			1	1125	1680	H (<i>home</i>)			2	240	540	H (<i>home</i>)			2	540	570	T (<i>traveling</i>)			2	570	1080	B (<i>business</i>)			2	1080	1110	T (<i>traveling</i>)			2	1110	1680	H (<i>home</i>)			<table style="border-collapse: collapse; margin-left: auto; margin-right: auto;"> <tr> <th style="border-right: 1px solid black;"><i>Id</i></th> <th style="border-right: 1px solid black;">240</th> <th style="border-right: 1px solid black;">241</th> <th style="border-right: 1px solid black;">242</th> <th style="border-right: 1px solid black;">...</th> <th style="border-right: 1px solid black;">1080</th> <th style="border-right: 1px solid black;">1081</th> <th style="border-right: 1px solid black;">1082</th> <th style="border-right: 1px solid black;">...</th> <th style="border-right: 1px solid black;">1110</th> <th style="border-right: 1px solid black;">1111</th> <th style="border-right: 1px solid black;">1112</th> <th style="border-right: 1px solid black;">1113</th> <th style="border-right: 1px solid black;">...</th> <th style="border-right: 1px solid black;">1679</th> <th>1680</th> </tr> <tr> <td style="border-right: 1px solid black;">1</td> <td>H</td> <td>H</td> <td>H</td> <td>...</td> <td>S</td> <td>S</td> <td>S</td> <td>...</td> <td>T</td> <td>T</td> <td>T</td> <td>T</td> <td>...</td> <td>H</td> <td>H</td> </tr> <tr> <td style="border-right: 1px solid black;">2</td> <td>H</td> <td>H</td> <td>H</td> <td>...</td> <td>T</td> <td>T</td> <td>T</td> <td>...</td> <td>H</td> <td>H</td> <td>H</td> <td>H</td> <td>...</td> <td>H</td> <td>H</td> </tr> </table>								<i>Id</i>	240	241	242	...	1080	1081	1082	...	1110	1111	1112	1113	...	1679	1680	1	H	H	H	...	S	S	S	...	T	T	T	T	...	H	H	2	H	H	H	...	T	T	T	...	H	H	H	H	...	H	H
<i>Id</i>	<i>Start Time</i>	<i>End Time</i>	<i>State</i>																																																																																																																																			
1	240	480	H (<i>home</i>)																																																																																																																																			
1	480	510	T (<i>traveling</i>)																																																																																																																																			
1	510	1050	B (<i>business</i>)																																																																																																																																			
1	1050	1080	T (<i>traveling</i>)																																																																																																																																			
1	1080	1110	S (<i>shopping</i>)																																																																																																																																			
1	1110	1125	T (<i>traveling</i>)																																																																																																																																			
1	1125	1680	H (<i>home</i>)																																																																																																																																			
2	240	540	H (<i>home</i>)																																																																																																																																			
2	540	570	T (<i>traveling</i>)																																																																																																																																			
2	570	1080	B (<i>business</i>)																																																																																																																																			
2	1080	1110	T (<i>traveling</i>)																																																																																																																																			
2	1110	1680	H (<i>home</i>)																																																																																																																																			
<i>Id</i>	240	241	242	...	1080	1081	1082	...	1110	1111	1112	1113	...	1679	1680																																																																																																																							
1	H	H	H	...	S	S	S	...	T	T	T	T	...	H	H																																																																																																																							
2	H	H	H	...	T	T	T	...	H	H	H	H	...	H	H																																																																																																																							

Figure 3.2.4: Information matrices of (a) flows, (b) presence, and (c) activity sequences. A flow matrix is calculated for each time unit.

- *Sequences matrix:* Analogous to a categorical sequence, the activity programs can be defined as a chronologically ordered list of n successive elements chosen from a finite alphabet Σ . Our alphabet contains the activities (i.e. states) represented as: H (home), L (leisure), S (shopping), ED (education), B (business), PB (personal business), ET (escort

trips), T (traveling). As mentioned earlier, we first converted the input dataset into a SPELL format table⁷, which rows correspond to stops and moves of individuals (see Figure 3.2.4c – top). In order to represent each sequence as a listing of its successive elements, we converted the SPELL data into STS (STate-Sequence) format, which is the internal format used by the TraMineR package⁸. It is one of the most intuitive and common way of representing a sequence, where the successive states (statuses) of an individual are given in consecutive columns, which correspond to a predetermined time unit (Gabadinho et al., 2009b). Thus, our resulting table arranges sequences as rows composed by elements (activities) in a one-minute scale within a time range from 240 to 1680 minutes (columns) (see Figure 3.2.4c – bottom).

3.3 Statistical Indicators and Typology

This section presents the process of derivation of statistical indicators and the typology of activity programs from the information matrices of flows, presence and sequences.

Indicators of travel flows and trips

Firstly, we extracted from the flow matrices of each time unit $t \in T$ and thematic attribute $a \in A$ the number of trips having each spatial location $s \in S$ as destination to derive the following indicators:

- the *mobility rate* (Eq. 3.3.1) of a location s at a time unit t is the count of trips taken during that time unit which destination is the spatial location s , divided by the same counting aggregate over 24 hours. Alternatively, the indicator can refer to the number of different movers traveling towards or internally that particular spatial location during that time unit; and

⁷A spell dataset have multiple observations for each subject, each covering a span of time (a spell) during which the subject is in a given state, such as traveling or a stop (Gabadinho et al., 2009b).

⁸TraMineR is a R-package for mining, describing and visualizing sequences of states or events, and more generally discrete sequence data (<http://traminer.unige.ch/>).

$$\frac{\text{count of trips during time } t}{\text{total count of trips over 24 hours}} \quad \begin{array}{l} 3.3.1 \\ \text{Mobility rate} \end{array}$$

- the *attribute share* (Eq. 3.3.2) of a location s at a time unit t is the number of trips performed during that time unit with the spatial location s as destination according to each attribute a (i.e. trip purposes and transportation modes), divided by the total count of trips having location s as destination during that time unit. Alternatively, the indicator can refer to the number of different movers traveling towards or internally the location s during that particular time unit per attribute a divided by the same counting for all attributes taken together.

$$\frac{\text{count of trips per attribute } a}{\text{total count of trips (all attributes taken together)}} \quad \begin{array}{l} 3.3.2 \\ \text{Attribute share} \end{array}$$

Secondly, we derive the indicators of flows magnitude and direction from the aggregation of *moves* between O/D locations $\langle s, s \rangle \in S \times S$ per trip purpose, transportation modes and all attributes taken together. The data complexity often generates dense O/D matrices, which hinder the design of efficient visualization techniques to represent it (Bahoken, 2016a). Furthermore, the study of travel flows focuses on the relationships between places rather than on their characteristics, which consequently leads analysts to assume a selection to ease interpretation (Giraud et al., 2016). Nystuen and Dacey (1961) proposed one of the first selection methods, so-called dominant flows, which allows to highlight the hierarchy between locations. Subsequently, several methods have been proposed to better reflect this intensity, one of the most frequently used being the so-called major flows, which selects only the most important flows, absolute or relative, either locally or globally (Giraud et al., 2016).

Particularly, we apply a local absolute selection of the k first flows from all origins to reduce the flow matrix to only the important flows. Based on the characteristics of our data (i.e. a great number of locations – the suburban districts – tend to produce a small amount of important flows, which are often towards the metropolitan area), we decided to use $k = 5$. We have chosen a local selection to allow the user to display flows for a subset of locations and/or for a particular time unit. In this case, a global selection would eliminate flows that are important within a subset formed by suburban areas, since the most

important flows were likely towards the metropolitan area that would not be currently represented, or during a time period when few trips were performed, since the global selection would keep the flows generated during the time periods when the most trips happened (e.g. during daytime).

Indicators of territory and population dynamics

The indicators that describe the territory are based on the estimation of people present in the different spatial locations over time determined by the counting of movers visiting each spatial location $s \in S$ at different time units $t \in T$, defined as follows:

- the *presence of movers* in the location s at the time unit t is defined as the count of different movers that visited the spatial location s during that time unit. The indicator can yet represent the aggregate count of different movers visiting the location s over 24 hours;
- the *presence of movers per activity* is defined as the count of different movers that visited the location s at each time unit t to perform each activity $a \in A$;
- the *activity share* (Eq. 3.3.3) of location s at the time unit t is defined as the count of different movers that visited the location s during the time unit t to perform the activity a divided by the total count of people visiting the location s during that time unit;

$$\frac{\text{count of people doing activity } a}{\text{total count of people visiting the location } s} \quad \begin{array}{l} \text{3.3.3} \\ \text{Activity share} \end{array}$$

- the *presence density* (Eq. 3.3.4) of a location s at the time unit t is defined as the proportion of people present in the location s during time unit t per square kilometer. The indicator also describes the average presence density of a location s over 24 hours;

$$\frac{\text{count of people present in the location}}{\text{location's surface in km}^2} \quad \begin{array}{l} \text{3.3.4} \\ \text{Presence density} \end{array}$$

- the *presence fluctuation* of a location s during the time unit t , is defined as the difference between the count of different movers that visited the

location s during the time unit t and the location's estimated population size. In the study of population dynamics, fluctuation represents the rise and fall of the number of individuals in a population over time according to births, deaths, arrival and departure of immigrants. We borrow the term to represent the temporal variation of individuals presence in a location relatively to the location's population;

- the *fluctuation rate* (Eq. 3.3.5) of a location s during the time unit t is the ratio of presence fluctuation measure of location s and the location's estimated population size; and

$$\frac{\left(\begin{array}{c} \text{count of people} \\ \text{present in the location} \end{array} \right) - \left(\begin{array}{c} \text{location's} \\ \text{population size} \end{array} \right)}{\text{location's population size}} \quad \begin{array}{l} 3.3.5 \\ \text{Fluctuation rate} \end{array}$$

- the *attractiveness* (Eq. 3.3.6) of a location s is calculated over 24 hours and refers to the aggregate number of different movers that visited the location s over 24 hours divided by the location's population size adjusted by the global value of this same ratio for the whole region. A value over 1 indicates the location's "real density" is greater than its population density, and a value under 1 indicates otherwise (André-Poyaud et al., 2008).

$$\frac{\left(\begin{array}{c} \text{count of people in} \\ \text{activity in the location} \end{array} \right)}{\left(\begin{array}{c} \text{location's} \\ \text{population size} \end{array} \right)} \times \frac{\left(\begin{array}{c} \text{region's} \\ \text{population size} \end{array} \right)}{\left(\begin{array}{c} \text{count of people in} \\ \text{activity in the region} \end{array} \right)} \quad \begin{array}{l} 3.3.6 \\ \text{Attractiveness} \end{array}$$

Typology of activity programs

As mentioned earlier, the daily trajectory of a mover corresponds to the sequence of spatial events (i.e. stops and moves) that establish the changes of the spatial position of that mover. Further, a set of thematic attributes allows to describe spatial events according to activities and transportation modes, and movers according to socio-demographic information. Hence, the daily trajectory of mover i can be defined as $D = \{S_i, T_i, A_i\}$, where $S_i \subset S$ contains the spatial locations the mover visited during the day, $T_i \subset T$ represents the set of time units that define the duration, starting and ending time of each

spatial event, and $A_i \subset A$ is formed by the set of activities and transportation modes associated to stops and moves, and the set of socio-demographic aspects associated to the mover. From each daily trajectory, we derive the following indicators:

- the *space-time path*, which comprises a collection of triples $\langle s, t, a \rangle \in S \times T \times A$, where s represents a visited location, t corresponds to the time unit when the visit took place, and a corresponds to an activity or transportation mode depending on whether the segment formed by the linking of two points $\langle s_i, t_i \rangle$ and $\langle s_j, t_j \rangle$ correspond to a move or a stop. In case the segment describes a stop, s_i and s_j correspond to the same spatial location, while in a move, s_i describes the origin and s_j the destination spatial location of the trip; and
- the *activity program*, which comprises a sequence of tuples $\langle a, t \rangle \in A \times T$, where a represents an activity, including the act of traveling from one place to another, and t represents the time unit when the activity took place.

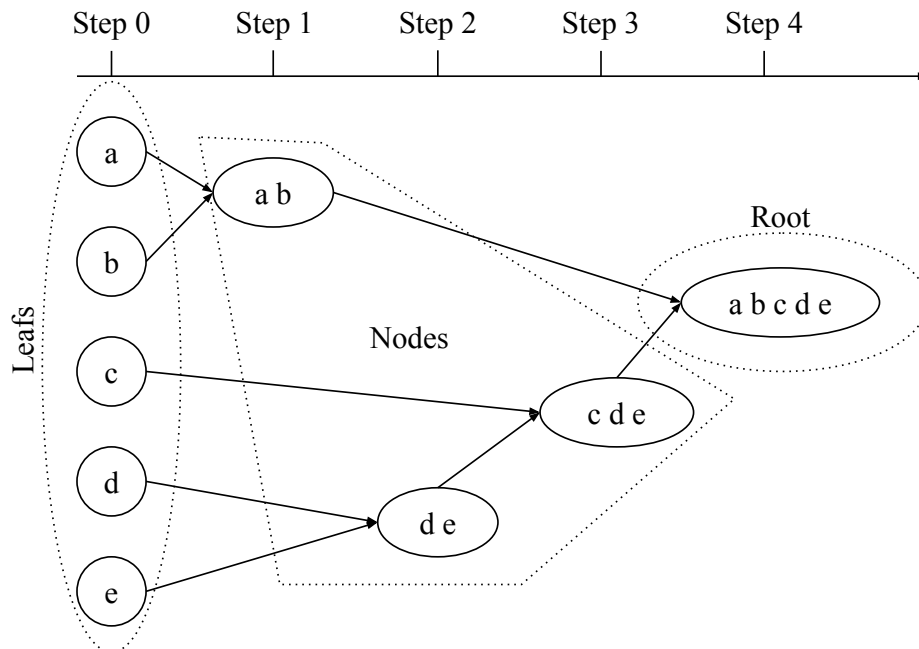


Figure 3.3.1: Workflow of AGNES algorithm. At each step, leafs are clustered together based on their similarity. Adapted from: [Kassambara \(2020\)](#).

The set of activity programs within each dataset (14,821 sequences for the region of Grenoble; 25,202 sequences for Lyon; and 10,096 sequences for Rennes) underwent a classification process that allowed us to extract a typology that describes the variety of daily activity programs within the data. The classification follows a hierarchical clustering based on the AGNES (Agglomerative Nesting) algorithm (Kaufman and Rousseeuw, 2009), which considers initially each element as a single-element cluster (leaf) and, at each step, combines the most similar clusters into a new bigger cluster (nodes). This procedure is iterated until all points are members of just one single big cluster (root) (see Figure 3.3.1). The classification process was performed with support of tools for mining and visualizing sequences of categorical data provided by TraMineR package (Gabadinho et al., 2011), and consists of the following steps (Kassambara, 2020):

1. *Computing dissimilarity information between every pair of sequences in the dataset.* This stage allows to decide which sequences (i.e. activity programs) can be grouped together based on their similarity. In social sciences, sequence analysis aims to uncover socio-temporal regularities in the data, where Optimal Matching (OM) is often the most used method. It determines the degree of dissimilarity between two sequences by the smallest number of operations that are necessary to turn one sequence into another. The allowed operations are insertion, deletion and substitution, which are penalized by a cost often equal to one. *Indel* (i.e. insertion and deletion) operations distort time in order to align identically coded events, which consequently destroy the temporal link between sequences, their contemporaneity (Lesnard, 2010).

	Low rate of unemployment			High rate of unemployment		
	1	2	3	4	5	6
<i>i</i>	E	E	E	U	U	E
<i>j</i>	U	U	E	E	E	E
<i>k</i>	E	E	E	E	E	E

Figure 3.3.2: Dynamic Hamming Distance: an example. Source: Lesnard (2009).

When analyzing daily activity programs, timing of everyday activities is crucial to keep the social structure of sequences, which means that what matters is not only the events but when they occur. This way,

identical events happening at distinct moments in time should be considered as different. Therefore, we chose to use the Dynamic Hamming Distance (DHD) method (Lesnard, 2010), which only uses substitution operations, which cost depends on the position t in the sequence, to determine the dissimilarity of sequences. The method is applicable when they are of equal length. Substitution costs reflect the penalty of replacing a state by another, i.e. the higher the penalty, the more different the states are. Let us exemplify it using the sequences i, j, k describing work stability with two states, employed (E) and unemployed (U) (Figure 3.3.2) (Lesnard, 2009). Using time-varying substitution costs, it is possible to define unemployment states to being closer to employment ones when the unemployment rate is high. For instance, if the employment rate is low at the beginning of the studied period ($t = 1, 2$) but high later, then the distance between j and k will be higher than the one between i and k because being unemployed at a time of full employment is more atypical than when unemployment is widespread. This also means that the distance between i and j will be higher than the one between k and j , even though i and j have more events in common, because those events occur at different dates with different rates of unemployment.

2. *Using linkage function to group sequences into hierarchical cluster tree based on the distance information.* Clusters that are in close proximity are linked together using a linkage function. We apply the Ward's method (Ward, 1963), which minimizes the total within-cluster variance. The clustering algorithm (Figure 3.3.1) uses the distance matrix (obtained in step 2) as input and merges clusters together based on whether their squared distance lead to a minimum increase in total within-cluster variance after merging. This procedure results in a hierarchical tree, with the number of clusters ranging from one to the number of sequences.
3. *Determining where to cut the hierarchical tree into clusters.* Dendrograms correspond to the graphical representation of the hierarchical tree generated by the clustering algorithm in step 3. We use the dendrogram derived from each dataset as a guide to determine the number of clusters in the typology of activity patterns (see Figure 3.3.3). Each leaf in the tree correspond to one sequence. As we move up the tree, similar sequences are combined into branches, which are themselves fused at a higher height. The height of the fusion, provided on the vertical axis, indicates the distance between two clusters. The higher the fusion's height, the less similar the clusters are. This information allows us to

choose a height where to cut the dendrogram to form clusters. Based on our hierarchical trees, we notice that they are mostly similar among datasets, so we cut at a height that results into 6 clusters, which we judge relevant to our analysis.

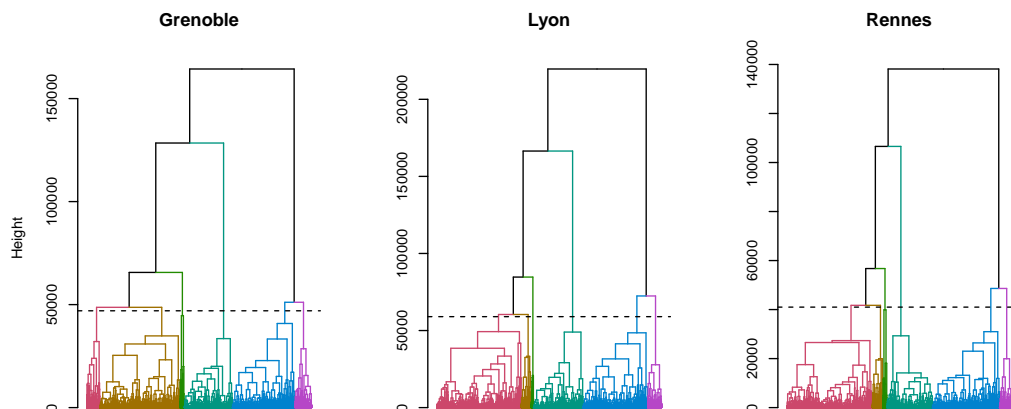


Figure 3.3.3: The dendrograms resulting from the hierarchical clustering performed on the sets of daily trajectories of Grenoble, Lyon and Rennes metropolitan areas. The dashed line represents the height where we cut each tree to extract the clusters of the typologies.

The resulting typology of activity programs of each dataset contains six clusters, which are significantly large considering the number of activity sequences used as input for the classification. A typical example are the clusters formed by programs where the main activity is studying or working, which correspond to a large part of programs within any dataset (see Appendix A for a complete description of clusters). Therefore, we summarize the clusters by extracting a group of representative patterns that cover all the spectrum of distinct sequences present in each cluster. We follow an algorithm proposed by [Gabadinho et al. \(2009a\)](#) which determines a representative set by (1) preparing a sorted list of candidate representative sequences based on a particular criterion and (2) eliminating redundancy within this list according to a similarity threshold. The method defines the coverage level of the representative set through a threshold, that is the percentage of sequences having a representative in their neighborhood. We define this threshold as 25% and extract four different representative sets according to the following criteria:

- *Neighborhood density*, which selects candidate sequences based on the number – the density– of sequences in their neighborhood. Given a

radius, which is by default the maximal theoretical distance between two sequences, the neighborhood density for each sequence in the set is obtained from the distance matrix by counting by row or column the number of distances that are lower than the established radius;

- *Centrality*, which identifies the most central sequence, i.e. the one with minimal sum of distances to all other sequences in the set. The resulting sequence is the *medoid*, a classical representative measure used in cluster analyses;
- *Frequency*, which determines candidate sequences according to their appearance frequency in the set. The more frequent a sequence, the more representative it is supposed to be. The frequency of each sequence in the set is obtained from the distance matrix by counting by row or column the distances that are equal to 0 (a distance of 0 between two sequences indicates they are equal); and
- *Likelihood*, which determines candidate sequences according to the probability with which each of its successive elements are supposed to occur at its position. The criterion considers the probabilities derived from the first order Markov model, which assumes the probability of an element occurring at its position depends only on the previous element's probability.

A set of representative trajectories allows to identify one or several programs that summarize the whole cluster, which enables the visual representation of only a set of sequences reducing visual cluttering while transferring the relevant information to the analyst.

Summary

Table 3.3.1 summarizes the statistical indicators and the typology of activity programs according to the objects of interest from which they were derived and the spatio-temporal granularity levels and thematic attributes over which they can be explored. Particularly, certain indicators of travel flows and trips, population and territory dynamics can be explored according to a particular group of people belonging to a cluster of the typology of activity programs. The typology group moves together according to similarities within their daily activity programs, which behavior could be generalized to the population they represent. Therefore, we consider these groups to be both an

<i>Object of Interest</i>	<i>Indicator</i>	<i>Space</i> ⁱ	<i>Time</i>	<i>Modes</i>	<i>Purposes</i>	<i>Socio-demographic</i>	<i>Group</i> ⁱⁱ
Trips	Travel flows	PD, IA, LA	One-hour, AGG ⁱⁱⁱ	Yes	Yes	No	No
	Mobility Rate	PD, IA, LA, AGG	One-hour, AGG	Yes	Yes	No	Yes
Territory and Population	Presence	PD, IA, LA, AGG	One-hour, 24h	No	Yes	No	Yes
	Presence Density	PD, IA, LA	One-Hour, AGG	No	No	No	Yes
	Presence Fluctuation	PD, IA, LA	One-hour, AGG	No	No	No	No
	Attractiveness	PD, IA, LA	AGG	No	No	No	No
Daily Trajectories	Typology of Activity Patterns	SA, AGG	5-minutes	Yes	Yes	Yes	Yes

ⁱ Territorial Partitions: Small Areas (SA); Polling Districts (PD); Intermediate Areas (IA); Large Areas (LA).

ⁱⁱ Group of individuals belonging to a particular cluster of the typology of activity patterns.

ⁱⁱⁱ AGG stands for all spatial locations or time units taken together as one single location or time unit.

Table 3.3.1: Summary of statistical indicators and the typology of activity patterns.

indicator that reveal the diversity and necessity of daily traveling according to individuals socio-demographic characteristics, and a filtering variable that enable to explore the variation of mobility and presence dynamics indicators over different population groups. Hereafter, we present a system of tasks to guide the exploration of indicators variation over the three dimensions of the data.

3.4 Querying

As mentioned earlier, there are three fundamental sets within the data (i.e. space, time and objects), which relationship can be established by the spatio-temporal triad framework of [Peuquet \(1994\)](#) (Figure 3.4.1 – left) through three basic kinds of questions:

- *when + where* → *what*: describe the object or set of objects that are present at a given location or set of locations at a given time or set of times
- *when + what* → *where*: describe the location or set of locations occupied by a given object or set of objects at a given time or set of times
- *where + what* → *when*: describe the time or set of times that a given object or set of objects occupied a given location or set of locations

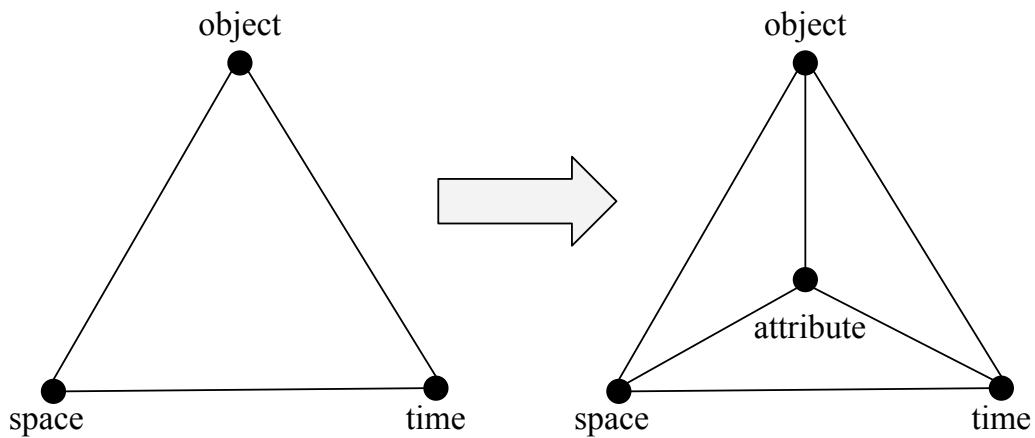


Figure 3.4.1: Overview of the Triad (left) and Pyramid (right) frameworks. Adapted from: [Peuquet \(1994\)](#), [Mennis et al. \(2000\)](#).

Further, the pyramid framework (Figure 3.4.1 – right) proposed by ([Mennis et al., 2000](#)) extends the spatio-temporal triad in order to allow the inclusion of a fourth dimension, the *theme*, which we refer in this work as thematic *attribute*. This dimension allows to describe the objects and spatial events according to socio-demographic aspects, activities and trip purposes, and transportation modes. Overall, the relationship among attributes and the fundamental sets of the data is established through four types of questions, defined as follows:

- *when + where + attribute* → *what*: describe the objects of set of objects described by a given attribute or set of attributes existing at a given location or set of locations at a given time or set of times;
- *when + what + attribute* → *where*: describe the location or set of locations occupied by a given object or set of objects described by a given attribute or set of attributes at a given time or set of times;

- *where + what + attribute* → *when*: describe a time or a set of times that a given object or set of objects described by a given attribute or set of attributes occupied a given location or set of locations; and
- *when + where + what* → *attribute*: give the attribute or set of attributes describing the object or set of objects existing at a given location or set of locations at a given time or set of times.

We used the definition of question levels proposed by [Andrienko et al. \(2008\)](#) to expand these basic questions and propose a set of user queries that are either *elementary* (Elem), which addresses elements of the reference set, or *synoptic* (Syn), which addresses sets of references that may be the whole reference set or subsets. Particularly, the overarching analysis supported by our framework consists in exploring the variation of the indicators of daily urban mobility over the Cartesian product of four dimensions $S \times T \times O \times A$, which inputs are defined as follows:

- the *spatial input*, which elementary components are single locations $s \in S$, and the synoptic element is the whole set S , which represent the whole urban area. The spatial locations forming the set S change according to the chosen territorial partition;
- the *temporal input*, which elementary components are single time units $t \in T$, and the synoptic element is the whole set T , which represent the 24 hours of a day. The time units change according to the chosen temporal granularity level;
- the *object input*, which elementary components are subsets of movers $O_i \subset O$, where i correspond to the number of a cluster of the typology to where belong the activity programs associated to the referred movers, or a spatial event $o \in O$, and the synoptic elements are the whole set of movers $O_m \subset O$ or the whole set of spatial events $O_e \subset O$; and
- the *attribute input*, which elementary components are single transportation modes, trip purposes, activities or socio-demographic aspects $a \in A$, and the synoptic components are subsets of attributes $\{A_a, A_m, A_p, A_s\} \subset A$ corresponding to the set of activities A_a , transportation modes A_m , trip purposes A_p , or socio-demographic aspects A_s , or the whole set of thematic attributes A .

Furthermore, we used the general querying schema introduced by Li et al. (2018) to propose the variation of indicators as a function $S \times T \times O \times A \rightarrow I$, where I represents the value of indicators according to the given space, time, object and attribute inputs. The system of tasks allows to treat elementary and synoptic tasks based on:

- time units $t \rightarrow (S \times O \times A \rightarrow I)$ or set of time units $\Sigma(T) \rightarrow (S \times O \times A \rightarrow I)$ (Table 3.4.1a);
- locations $s \rightarrow (T \times O \times A \rightarrow I)$ or set of locations $\Sigma(S) \rightarrow (T \times O \times A \rightarrow I)$ (Table 3.4.1b);
- thematic attributes $a \rightarrow (T \times S \times O \rightarrow I)$ or the set of thematic attributes $\Sigma(A) \rightarrow (T \times S \times O \rightarrow I)$ (Table 3.4.1c);
- objects $o \rightarrow (S \times T \times A \rightarrow I)$ or set of objects $\Sigma(O) \rightarrow (S \times T \times A \rightarrow I)$ (Table 3.4.1d);
- any combination of two dimensions of the data, enabling the exploration of indicators over the remaining two dimensions, e.g., $S \times T \rightarrow A \times O \rightarrow I$ (Table 3.4.2).

Furthermore, there may be questions comparing indicators over multiple locations, time units, objects or attributes. Hence each task can be split into two sub-types of tasks: identification and comparison (Andrienko et al., 2003), according to the input level. For instance, let us take $t \rightarrow (S \times O \times A \rightarrow I)$, where the temporal input is a time unit. One could formulate the following tasks:

- Compare the value of indicator I for object o and attribute a , or different objects and attributes at locations l_1 and l_2 ;
- Compare the value of indicator I at location l considering the attribute a or different attributes, and the objects o_1 and o_2 ; and
- Compare the value of indicator I at location l considering the object o or different objects, and the attributes a_1 and a_2 .

This collection of tasks are performed within our visualization framework through *selection* operations that enable one to explore the variation of indicators over any combination derived from the structure $S \times T \times O \times A$ by

		Objects	
Space	<i>Elem</i>	What is the value of the indicator I at spatial location s regarding the object o and the attribute a ?	What is the value of the indicator I at spatial location s regarding different objects and attributes?
	<i>Syn</i>	What is the spatial distribution of the indicator I regarding the object o and attribute a ?	What is the spatial distribution of the indicator I for different objects and attributes?
		<i>Elem</i>	<i>Syn</i>
Attributes			
(a) Tasks based on time units $t \rightarrow (S \times O \times A \rightarrow I)$ or set of time units $\Sigma(T) \rightarrow (S \times O \times A \rightarrow I)$.			
		Objects	
Time	<i>Elem</i>	What is the value of the indicator I at time unit t regarding object o and attribute a ?	What is the value of the indicator I at time unit t considering different objects and attributes?
	<i>Syn</i>	What is the temporal variation of indicator I considering the object o and attribute a ?	What is the temporal variation of indicator I for different objects and attributes?
		<i>Elem</i>	<i>Syn</i>
Attributes			
(b) Tasks based on locations $s \rightarrow (T \times O \times A \rightarrow I)$ or set of locations $\Sigma(S) \rightarrow (T \times O \times A \rightarrow I)$.			
		Objects	
Space	<i>Elem</i>	What is the value of the indicator I at spatial location s and time unit t regarding object o ?	What is the temporal variation of the indicator I at spatial location s regarding different objects?
	<i>Syn</i>	What is the spatial distribution of the indicator I at time unit t regarding the object o ?	How the spatial distribution of the indicator I regarding different objects varies from time to time?
		<i>Elem</i>	<i>Syn</i>
Time			
(c) Tasks based on thematic attributes $a \rightarrow (T \times S \times O \rightarrow I)$ or the set of thematic attributes $\Sigma(A) \rightarrow (T \times S \times O \rightarrow I)$.			
		Attributes	
Space	<i>Elem</i>	What is the value of the indicator I at spatial location s and time unit t regarding attribute a ?	What is the temporal variation of the indicator I at spatial location s regarding different attributes?
	<i>Syn</i>	What is the spatial distribution of the indicator I at time unit t regarding the attribute a ?	How the spatial distribution of the indicator I regarding different attributes varies from time to time?
		<i>Elem</i>	<i>Syn</i>
Time			
(d) Tasks based on objects $o \rightarrow (S \times T \times A \rightarrow I)$ or set of objects $\Sigma(O) \rightarrow (S \times T \times A \rightarrow I)$.			

Table 3.4.1: Tasks for exploring the variation of indicators over three dimensions of the data.

		Objects	
Attributes	<i>Elem</i>	What is the value of indicator I regarding the attribute a and the object o ?	What is the value of indicator I regarding the attribute a for different objects?
	<i>Syn Elem</i>	What is the attribute share of indicator I regarding the object o ?	What is the attribute share of indicator I regarding different objects?
(a) Tasks based on time units or set of time units and locations or set of locations, overall defined as $T \times S \rightarrow O \times A \rightarrow I$			
		Objects	
Space	<i>Elem</i>	What is the value of indicator I at spatial location s regarding the object o ?	What is the value of indicator I at spatial location s regarding different objects?
	<i>Syn Elem</i>	What is the spatial distribution of indicator I regarding the object o ?	What is the spatial distribution of indicator I regarding different objects?
(b) Tasks based on time units or set of time units and attributes or set of attributes, overall defined as $T \times A \rightarrow S \times O \rightarrow I$			
		Objects	
Time	<i>Elem</i>	What is the value of indicator I at time unit t regarding the object o ?	What is the value of indicator I at time unit t regarding different objects?
	<i>Syn Elem</i>	What is the temporal variation of indicator I regarding the object o ?	What is the temporal variation of indicator I regarding different objects?
(c) Tasks based on locations or set of locations and attributes or set of attributes, overall defined as $S \times A \rightarrow T \times O \rightarrow I$			
		Attributes	
Space	<i>Elem</i>	What is the value of indicator I at spatial location s regarding the attribute a ?	What is the value of indicator I at spatial location s regarding different attributes?
	<i>Syn Elem</i>	What is the spatial distribution of indicator I regarding the attribute a ?	What is the spatial distribution of indicator I regarding different attributes?
(d) Tasks based on time units or set of time units and objects or set of objects, overall defined as $T \times O \rightarrow S \times A \rightarrow I$			
		Attributes	
Time	<i>Elem</i>	What is the value of indicator I at time unit t regarding the attribute a ?	What is the value of indicator I at time unit t regarding different attributes?
	<i>Syn Elem</i>	What is the temporal variation of indicator I regarding the attribute a ?	What is the temporal variation of indicator I regarding different attributes?
(e) Tasks based on locations or set of locations and objects or set of objects, overall defined as $S \times O \rightarrow T \times A \rightarrow I$			
		Space	
Time	<i>Elem</i>	What is the value of indicator I at time unit t and spatial location s ?	What is the spatial distribution of indicator I at time unit t ?
	<i>Syn Elem</i>	What is the temporal variation of indicator I at spatial location s ?	What is the spatio-temporal variation of indicator I ?
(f) Tasks based on attributes or set of attributes and objects or set of objects, overall defined as $A \times O \rightarrow T \times S \rightarrow I$			

Table 3.4.2: Tasks for exploring the variation of indicators over two dimensions of the data.

selecting elements of one or two of these dimensions as the query input. The analyst has autonomy to use these queries to conduct the analysis as they consider appropriate to their needs; no specific exploration flow is imposed within our framework.

A set of visual and interaction tools support these selection operations through an one-to-many relation from a mobile-based interface that leverages tactile and tangible input to improve multivariate data exploration. The remaining of this chapter describes the design rationale and implementation of our visual and interaction tools, while establishing the relationship of system of tasks and the visual analysis.

3.5 Interactive Visualization

The visual interface should be able to represent indicators describing trips and travel flows, the territory, and daily trajectories defined over four heterogeneous dimensions of the data (i.e. space, time, objects, and theme). The data representations need to reflect their inherent properties (i.e. the geographical arrangement of locations and the ordering of time units), and the interaction tools should enable the querying of indicators through the system of tasks defined earlier. Therefore, considering concerns and guidelines evoked by [Baldonado et al. \(2000\)](#) regarding the use of multiple views, we assume that these are necessary to provide an efficient visual analysis of urban mobility data.

We deal with data records that are defined over multiple dimensions, describing human movements through various thematic attributes (i.e. trip purposes, transportation modes, and socio-demographic aspects), which are themselves linked to multiple spatio-temporal granularity levels. Therefore, we aim to design a system that allows the analyst to perform different types of analysis, each one focusing on a distinct and complementary object of interest within the data, which exploration and comparison of derived indicators should be possible over multiple spatio-temporal granularity levels and thematic attributes. The easiest and fastest way to provide such comparison is by displaying views side-by-side, while also reducing the dependency on user's memory due to the possibility of presenting all the important information at a glance.



Figure 3.5.1: Overview of eSTIME visualization interface.

These requirements evoke the necessity of a large visualization space and flexibility to visualize the data from different perspectives. Nonetheless, considering that our potential end-users may not have access to large high-resolution displays at their everyday work environment, we opted for a disperse visualization over multiple linked conventional displays (e.g., desktop monitors) (see Figure 3.5.1). Depending on the ongoing analysis, one may not have to deal with all indicators at once, or with every possible spatio-temporal combination. Therefore, each display embeds a customizable analytical dashboard that can be progressively filled out with visual representations of indicators built over locations, time units, objects and attributes that the analyst considers appropriate to their analysis.

We assume that, as the number of conventional displays increase, the interaction might not be comfortable through traditional mouse- and keyboard-based techniques. Therefore, our system includes a one-to-many interaction from a mobile-based interface, which leverage tactile and tangible input to

control the set of views dispersed over one or multiple analytical dashboards. The tangible interaction serve to control the temporal animation of indicators by tilting the device, which resulting angle is mapped to time units on a virtual time picker.

The remaining of this section is organized as follows. Subsection 3.5.1 describes the visual representations chosen for visualizing each indicator. Subsection 3.5.2 presents the movement-based interaction interface we designed for improving map reading while using time animation. Subsection 3.5.3 presents the interaction mechanisms that enable to query indicators over space, time, objects and attributes enabling the use of our system of tasks (see Section 3.4 for more information). Subsection 3.5.4 describes the provenance mechanism included in our approach to enable the understanding on which flows of analysis are relevant to the domain and supported by our framework. Finally, Subsection 3.5.5 details the technical aspects of our implementation.

3.5.1 Visual Encoding

On top of the inherent complexity of the data and indicators, our environment combines customizable dashboards embedded into multiple displays and a non-conventional interaction interface based on a mobile device. In order to simplify the analysis, we follow a uniformity principle (Li et al., 2018). The design of our views follows a similar layout of display elements and components. Colors, fonts, labeling and other kinds of visual marks are consistent across the views. For categorical data, i.e. activities and transportation modes, we are using a single legend per dashboard to reduce visual cluttering, since colors are common across different views. We use the ColorBrewer tool (Harrower and Brewer, 2003), which provides color advice for cartography, to define the color schemes in our visualizations.

Nowadays, there are a variety of visual techniques designed to represent the most diverse perspectives to movement data. The reasoning behind the choice of visualization techniques does not considers only the novelty of a method, but its effectiveness to represent the data. Classic representations such as maps are powerful tools to represent a spatial situation, while being well known to our prospect users. Thus, they are considered into our design. We implemented a set of six visualization techniques to represent our set of indicators. The map is the only view that represents the geographical information and serves, therefore, as a spatial reference to the remaining views. Since every indicator

is defined over different locations and time units, multiple versions of a view may be displayed for a different version of the corresponding indicator. As well, they may be animated to represent the indicator at different time units.

Map View

Maps have been used over a hundred years to represent information over the geographical space. We visualize indicators summarizing the dynamics of different locations over time through choropleth and proportional symbols maps. The former enables encoding indicators which values correspond to a ratio (i.e. activity and fluctuation rate), while the latter are used for encoding indicators which value corresponds to a count (i.e. presence of movers and fluctuation).

In the choropleth maps, color shades encode values of presence density, attractiveness, activity (Figure 3.5.2a) and fluctuation rates. Two different diverging color schemes are used to represent the variance of fluctuation and attractiveness indicators, which neutral value is coded in white. Shades of blue encode negative values of fluctuation, which represent the amount of people present in the location that is negatively proportional to the population size, while shades of red encode the positive values representing otherwise (Figure 3.5.2b). The attractiveness indicator diverges around the value 1, which higher values are coded in shades of brown, indicating the “real density” of the location is greater than the population density, and lower values are coded in shades of green indicating the opposite. The remaining indicators are encoded by linear color schemes, where darker colors indicate higher values (i.e. closest to the extremity of that scale either negative or positive).

In the proportional symbol maps, each location is overlaid by a circle which size encodes the indicator’s value at each time unit. The color encodes activity, if one chooses to visualize the presence of movers per activity (Figure 3.5.2c). Otherwise we use purple to represent the total count of movers present in each location. The presence fluctuation is represented in red and blue to encode positive and negative values, respectively. In this case, larger blue circles encode lower values, and larger red circles otherwise (Figure 3.5.2d).

The legends are consistent throughout different time units, which colors and circle dimensions are based on the absolute minimum and maximum values for every location and time unit.

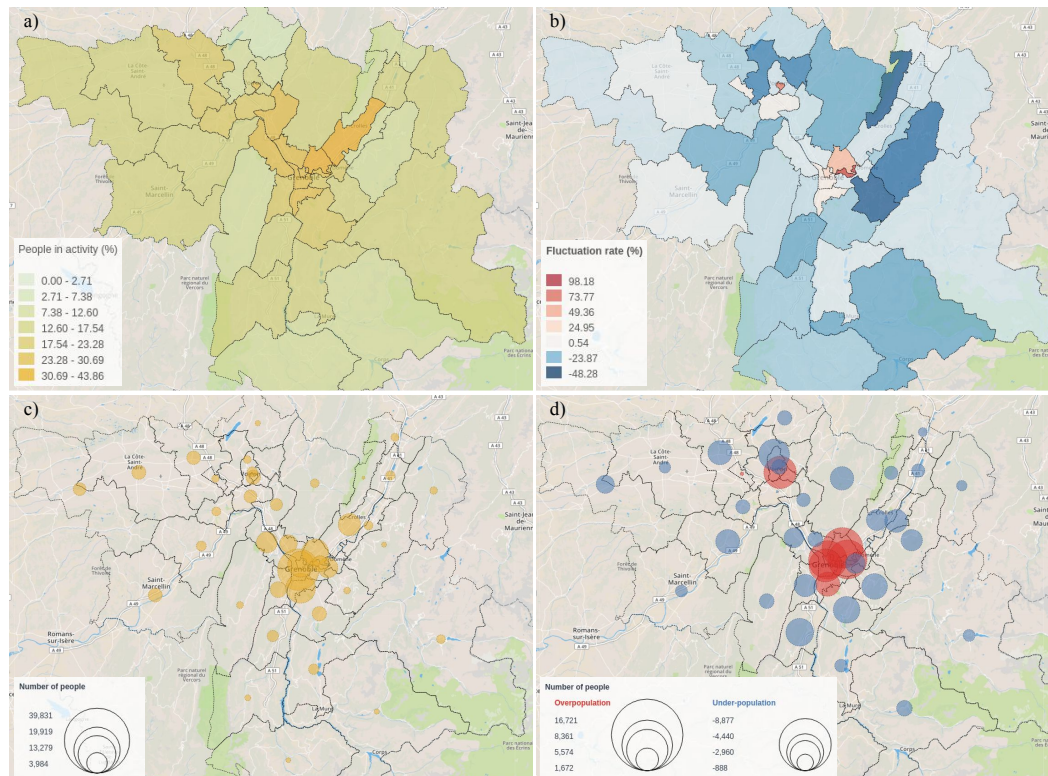


Figure 3.5.2: The maps represent indicators of business and fluctuation rates via the choropleth technique (top) and the presence of movers for business activity and fluctuation in different locations via the proportional symbols technique (bottom).

Mobility Wheel

A common approach in the analysis of mobility data is to represent why and how people travel. In this context, we could represent the attribute share indicator over 24 hours for the whole territory or a particular spatial location through simple visualization techniques, such as the pie chart. However, this information varies over different times of the day and understanding this variation is important to provide investments that are consistent to the real rhythms of the urban area.

Since daily mobility patterns tend to repeat themselves each 24 hours, cyclic representations of time are common in the literature. Particularly, timewheels are largely used to represent movement patterns around the clock. Inspired by [Zhao et al. \(2008\)](#) and [Zeng et al. \(2017\)](#), we append a double-ring donut chart to the pie chart representing the attribute share over 24 hours,



Figure 3.5.3: The *Mobility Wheels* representing the mobility rate indicator of *Oisans*, a suburban district in the region of Grenoble, along with attribute share (trip purposes (top) and transportation modes (bottom)). The donut charts display the attribute rate aggregate over 24 hours (bottom) or magnifies the indicator for a particular time interval (top). The gray rectangles encode time units when no movement was recorded.

to represent the variation of a particular location’ mobility rate over time (Figure 3.5.3). The rings are segmented into 24 rectangles, one for each time unit. The outermost ring encodes the mobility rate of a particular location, while the innermost ring displays the attribute share based on trip purposes or transportation modes. Further to displaying the attribute share over 24

hours, the central pie chart can display this indicator for a particular time unit, which serve as a lens to magnify the indicator and contribute to prevent misinterpretation of information due to the small size of each attribute partition inside the rectangles.

Upon demand, one can have detailed information on the displayed indicator (Figure 3.5.3 – top left corner of each chart). In this thesis, the indicators represented by the Mobility Wheel are calculated based on the number of people traveling towards or internally each spatial location. Therefore, for a particular time interval (i.e. a time unit or over 24 hours), we provide the total count of people traveling towards or inner the chosen location and the part of the region’s population that count represents. We also present detailed information on the distribution of these people per attribute, which information consists on the counting of individuals traveling there and the proportion of people that is represented by that count.

Both indicators (i.e. mobility and attribute rates) take only *different* movers into account, which causes people who made several trips to that location under the referred time interval to be counted only once. Therefore, we also provide the number of individuals that perform several trips for different purposes or using various transportation modes. This information allows the analyst to estimate the amount of trips those people represent, which actual value can be retrieved by exploring travel flows indicators (below).

Flows Diagram

Flow maps are a widely used technique to represent magnitude and direction of flows within a territory. However, the unchangeable property of geographical positions is a constraint on the design of legible maps, i.e. that avoid the so-called *spaghetti effect*, which makes it challenging to represent travel flows without losing the spatial component, while avoiding occlusion (Bahren, 2016b). The multi-display property of our system enables one to keep a geographical map visible on the mobile device during the whole analysis (details in Subsection 3.5.3). Therefore, we chose to represent flows by removing the geographical space.

We use a chord diagram, a graphical method typically used to display the inter-relationships between entities (called nodes). Their format can be aesthetically pleasing and they are quite popular in data visualization (Abel,

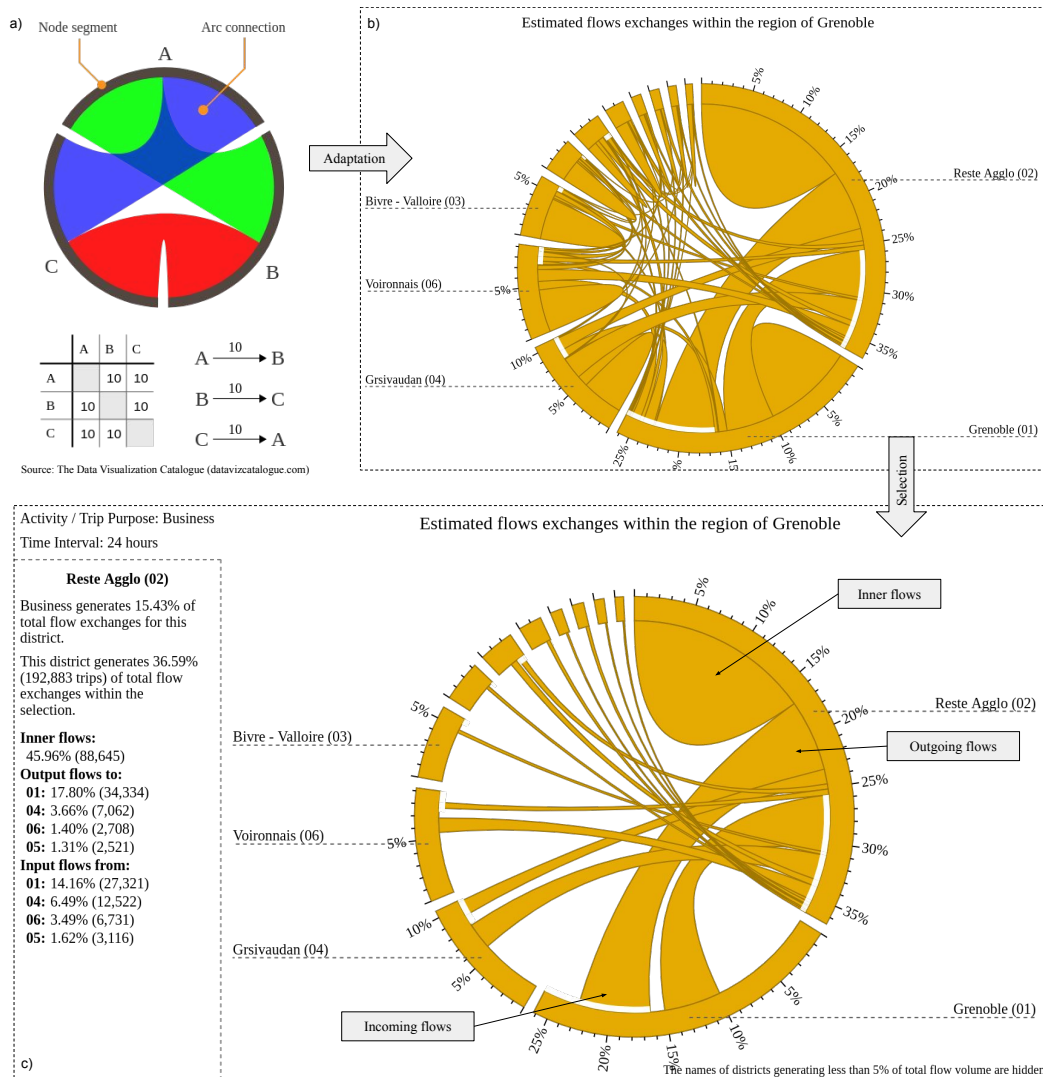


Figure 3.5.4: The *flows diagram* is based on a chord diagram, which arcs represent nodes and ribbons connect related nodes (top left). The figure represents the estimated flows exchanges within Grenoble’s inter-municipalities (12 districts) for business (top right). Upon selection, the connections of a particular location are highlighted and details on flow exchanges for that locations are displayed (bottom).

2018, Shi et al., 2018). Figure 3.5.4a presents a simple diagram to portray the relationship between entities A, B and C defined in a matrix (bottom of the image). The nodes are arranged along a circular axis, connected to each other either through ribbons or Bézier curves. The values are assigned to each connection, encoded by the size of each arc.

Applied to travel flows, the arcs along the axis represent spatial locations (Figure 3.5.4b), which are sorted in a descending order according to the total volume of flows generated per location within the selection. The ribbons' thickness describe the volume of flows exchange between locations, and color encodes trip attributes (i.e. purpose or transportation mode). To improve readability, the destination of flows are indicated through a white gap between the arc and ribbons. Thereby, each flow originates in the location which ribbon touches the arc, and the flows generated by trips inside the location's territory are represented through a half circle (i.e. a ribbon which origin and destination are the same).

By default, the view portray flows exchanges between every location within the whole region. Filtering tools are available to select meaningful sets of locations, either one location which connections are detected to generate the diagram, or a set of up to 10 locations selected by means of direct touch on the geographical map. Regardless the spatial selection, only the five (if possible) stronger connections are kept to avoid over-cluttering.

Interaction tools allow the user to highlight the connections of a particular location by directly selecting it on the map (Figure 3.5.4c). If the details panel is enabled, the user can see detailed information on the flows exchanges regarding the selected location. We provide the total amount of incoming, outgoing and inner trips regarding that location. In case the diagram represents travel flows for a given trip purpose or transportation mode, we inform the amount of trips that is generated for that attribute.

State Distribution Plot

For a particular location or the whole region, the *state distribution plot* displays the proportion of individuals per attribute over time while traveling or performing an activity there (Figure 3.5.5). It is a percentage stacked area chart, which x -axis represents time (24 hours) and y -axis gives the estimated proportion of movers per attribute, either per activity when present in that location or per transportation mode when traveling towards or inner the location.

To improve readability, we display horizontal and vertical grid lines identifying two-hours periods, while a gray bar follows the temporal selection created by animation or a time unit selection by means of direct touch. By default,

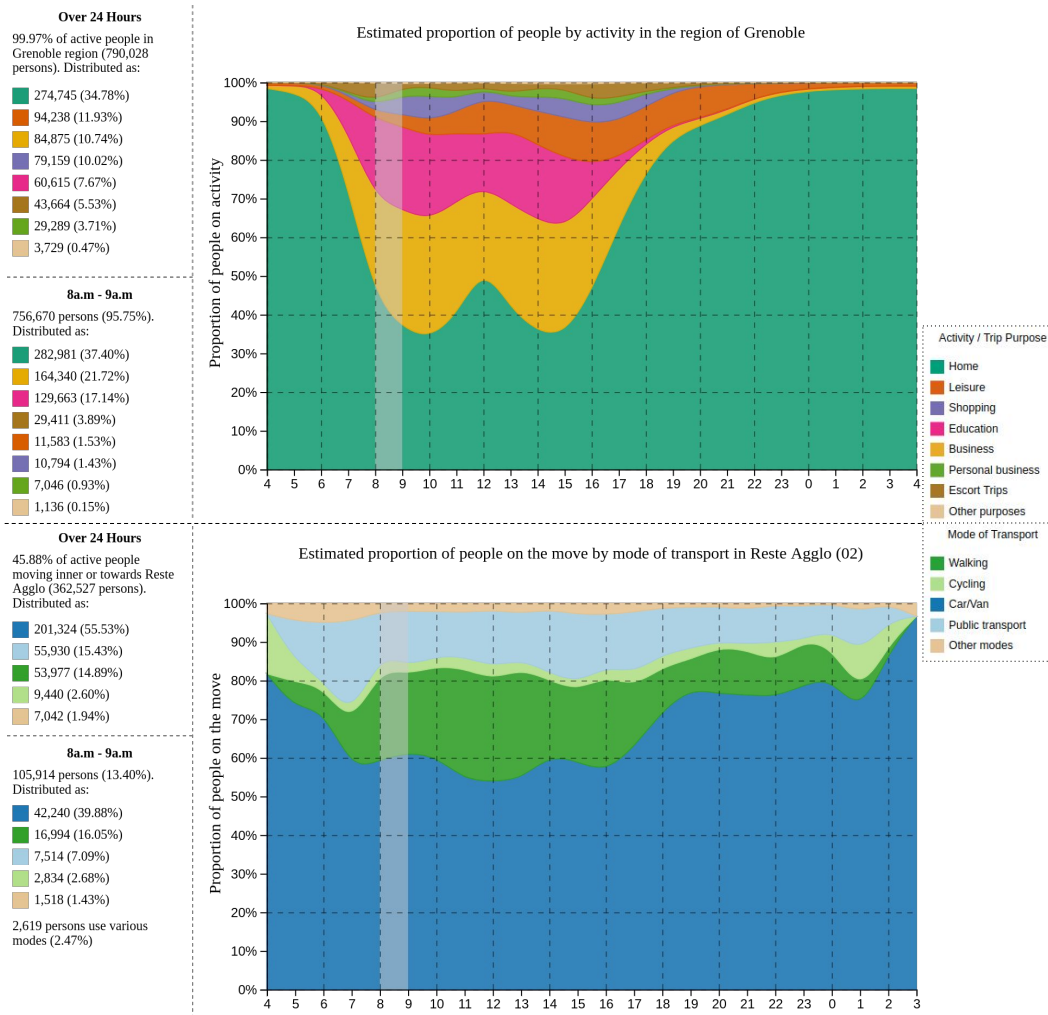


Figure 3.5.5: The *state distribution plot*. The *x*-axis represent time and the *y*-axis represents the indicator of either attribute or activity share.

it displays the activity rate for the whole region. Filtering tools enable the user to change the indicator to display the mobility rate per transportation mode, and to visualize either indicators for a particular location or for a group of individuals from the activity patterns typology. For the latter, values are adjusted so that the individuals represent a “real” part of the population.

Upon demand, one can have detailed information on the indicator both aggregate over 24 hours and regarding the current selected time unit. The first piece of information is the number of different movers visiting the location or traveling there and the part of the region’s population they represents. The second information gives the number of people per activity or transportation mode and the proportion of people that number represents. We also indicate

the count and proportion of people who perform multiple trips for different activities or using different transportation modes.

Sequence Index Plot

The *sequences index plot* is used to give the analyst a representation of qualitative sequence patterns within relatively homogeneous sets of sequences (Fasang and Liao, 2014). It is implemented on a basis of an horizontal proportional stacked bar chart, which y -axis represents the individuals. Within a daily trajectory, stops and moves may last less than one hour, we therefore use a time granularity in 5-minutes intervals to better encode them. However, to keep visual uniformity, the x -axis presents time through a granularity of one-hour intervals, from 4am (the day before) to 4am (the survey day).

Each segment between a 5-minute interval and the next one is colored to encode the activity of a stop or the transportation mode used to travel from one location to another. By default, the plot displays every daily trajectory in the dataset with color encoding activity. Filtering tools enable the user to select a group of individuals clustered together by the typology from which to display the activity programs and to choose which thematic information the color encodes. In case the plot is set to represent activities, gray encodes the action of traveling without discriminating transportation modes. Likewise, when the latter is represented, gray encodes the action of being on a stop, without activities distinction.

The sequences index plots in Figure 3.5.6 display the activity programs of individuals in the second group of the typology (Grenoble's dataset) with color encoding activities (top) and transportation modes (bottom). To improve readability, we draw vertical grid lines identifying two-hours time intervals, and a gray bar follows the time unit selection performed by means of direct touch or animation to retain one's attention on the data corresponding to the current time unit.

Upon demand, a details panel displays information to summarize the profile of individuals (i.e. age, gender, working hours, shift and status), which help to characterize and understand the typology's patterns. We highlight certain information in blue or red according to whether that aspect is under- or over-represented in relation to the average profile of all individuals in the dataset. For instance, we observe in Figure 3.5.6 that, for the selected group, people

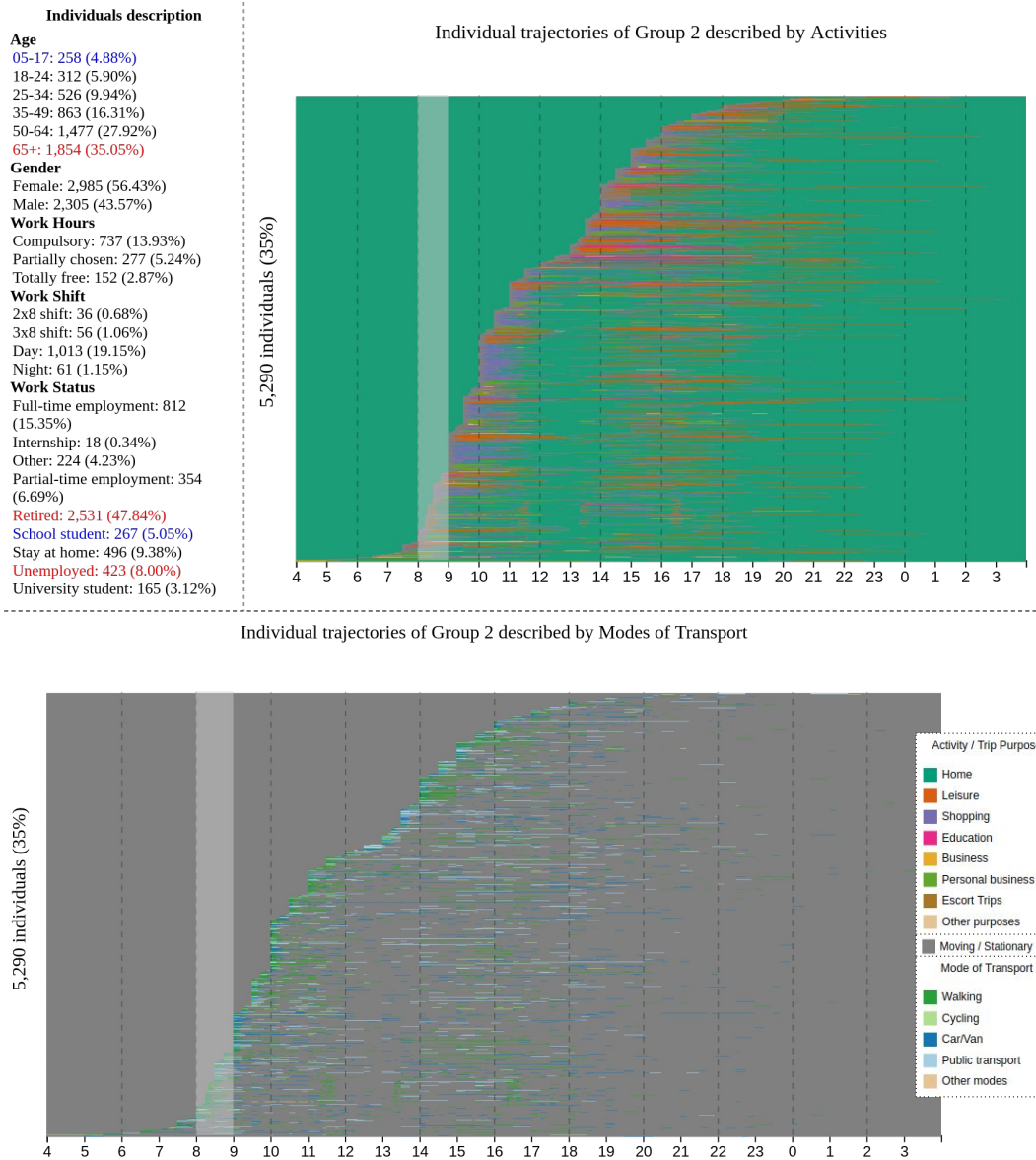


Figure 3.5.6: The *sequences index plot*. The *x*-axis represents time from 4am (the day before) to 4am (the survey day) and *y*-axis the individuals. Color encodes activities (top) of stops and transportation modes of moves (bottom). Gray encodes the time period when the individual was traveling (top) or stationary (bottom). The details panel (left) displays information that describe the profile of individuals.

aged 65 and plus, either retired or unemployed are over-represented (red), while children aged 17 and less, mostly school students are under-represented (blue). We consider a profile to be over-represented if the count of individuals in that group is higher than the average plus standard deviation of people in

all groups taken together, and under-represented otherwise (i.e. lower than the average minus standard deviation).

Space-time Cube

Despite the visual cluttering triggered by displaying a great number of trajectories in the STC, [Gonçalves et al. \(2016\)](#) showed that this visualization works well together with 2D representations. Therefore, considering its potential to explore data in space and time simultaneously, we use a classical 3D representation of the *STC*, which height represents time and the 2D plan depicts the space. This visualization is the result of a collaborative work with Michael Ortega⁹ from the PIMLIG team of the *Laboratoire d'Informatique de Grenoble*.

The spatial locations within our dataset are identified as named spatial features. Therefore, we estimated seven GPS coordinates within each spatial feature to map all possible activities performed in each location, which allowed to encode line segments with the color that represents the activity performed at stops. The choice of seven points intends to avoid overlapping segments which activities were performed at the same spatial location and, therefore, making it impossible to visually identify these activities. Furthermore, since the survey's goal consists on studying the mobility within a urban area, every trip which origin or destination corresponds to locations outside the urban area have these locations coded as a single random point that goes beyond the geographical limits of the urban area under study. Since the coordinates are the same for every trip under these conditions, representing it on the cube would clutter the visualization. Hence, we removed these trips, and therefore, the daily trajectories that included them from the data visualized in the STC.

We display space-time paths in a 5-minutes temporal granularity to better detail stops and moves. Nevertheless, to maintain visual uniformity, the height displays time as one-hour intervals from 4am (the day before) to 4am (the survey day). Likewise, the spatial information correspond to the territorial partition in small areas to give a more accurate representation of the spatial shape of trajectories. Thematic information are encoded through colored segments between two spatio-temporal points representing the activities and/or transportation modes ([Chen et al., 2011](#)). The user can choose whether the color encodes activities, transportation modes or both. Further, we use gray

⁹<http://iihm.imag.fr/en/member/ortega/>

to encode the temporal gaps when the mover was traveling from one place to another if color encodes activities, and to encode the time intervals when the mover was stationary if color encodes transportation modes (Figure 3.5.7).

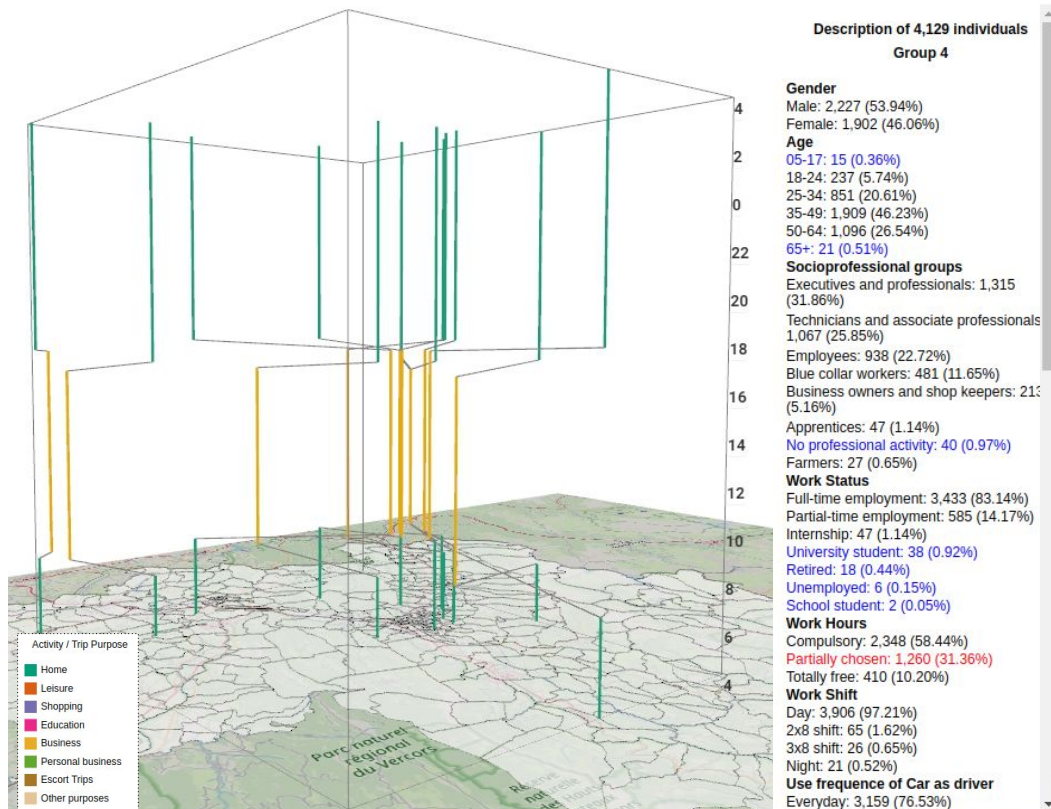


Figure 3.5.7: The representative trajectories of the typology's fourth group. The 2D plane represents the territory of the urban area partitioned into small areas, while the height presents time as one-hour intervals. The color encodes activities of stops. The details panel (right) displays information that characterized the movers.

To reduce visual cluttering, we display only the representative trajectories of each group in the typology. By default, the trajectories of all groups are displayed together, and color encodes activities. Filtering tools enable the user to choose which trajectories to display based on users' socio-demographic aspects (i.e. age, gender, work status), the typology's groups (more than one can be visualized together) and/or the criterion used to extract the representative sequences. One can use interaction tools to rotate, translate, zoom in/out the view, and to select trajectories directly touching on them, which provides spatial information by highlighting the locations visited by the individual(s) along the day. Further, if sequences index plots are being displayed in one or

more analytical displays, the corresponding sequence(s) are also highlighted in those views.

Users can also enable a details panel, which presents aggregate socio-demographic aspects of represented individuals according to the groups they belong (Figure 3.5.7 – right). Further to age, gender and work status, we provide information on socio-professional categories and the use frequency of certain transportation modes, which types depend on the data set of each urban area.

3.5.2 TiltingMap

Animation is largely used to explore data over time regardless the underlying visualization technique. It consists on presenting a sequence of time slices one at the time analogously to the process of assembling image frames into a movie file. Animations are preferable over time juxtaposing because they enable the representation of multiple charts while saving screen space. They have been shown to improve performance on memory-recall and map-reading when compared to static graphs (Harrower, 2001). However, they are heavily dependent on human's memory, which make them sometimes difficult to follow and understand the changes between data slices. Tversky et al. (2002) showed that most of the so-called successful applications of animation were likely a consequence of better visualization or study procedures such as interactivity or prediction that are known to improve learning independent of graphics. The same authors suggest the perceptual and cognitive limitations in the processing of a changing visual situation reduces the benefits of animation. Therefore, interactive techniques such as speed control, stop and start, zoom in and out, are essential to effectively support knowledge extraction through animation.

Although the use of multiple customizable analytical dashboards already enables the temporal comparison of indicators through the juxtaposition of visualizations displaying data for different time units, we understand that not all users dispose of multiple displays to compare several indicators or spatio-temporal combinations. One of our goals is to provide a flexible visual interface to the user, which includes a range of interaction techniques from which the user can choose the one that better fit their needs, e.g. based on cognitive demand and/or technological setup. Taking into account the drawbacks of animation, particularly the negative effects of animated choropleth maps, such

as color blindness (Fish et al., 2011), we designed a movement-based animation technique that aims to improve user experience by providing more control over animation, starting and ending it at different points in time and leveraging the position and orientation of their hands and wrists as a reference to recall the spatial situation depicted by the map on each time slice.

We designed this movement-based interface, called *TiltingMap*, on the basis of a tablet which serve as actuating lever for the tilting movement that controls time. The interface implements the metaphor of *lenticular images* in a way that each time slice appears from a different viewing angle triggered by tilting the device. Lenticular images are pictures made using the lenticular printing technique, which combines a set of images with lenticular lenses to produce printed images with an illusion of depth, or the ability to change or move as the image is viewed from different angles.

One can create both 2D and 3D effects using lenticular foils, i.e. translucent plastic sheets with one smooth side and another made of lenticules, which are small convex lenses that allow the transformation of a 2D image into a variety of visual illusions. Up to this date, the technique has been mostly used to display information through the so-called *true-3D*, which allows one to display 3D effects without the use of specific devices such as glasses. In the literature, we see applications of this technique on tourism through the interactive map proposed by Buchroithner et al. (2010), which displays touristic places in the region of Granatspitz Massif in the Eastern Alps, and the map of Manhattan city by Wagman (2009), which shows the New York's subway system, the neighborhood, and the streets grid depending on the viewer's angle.

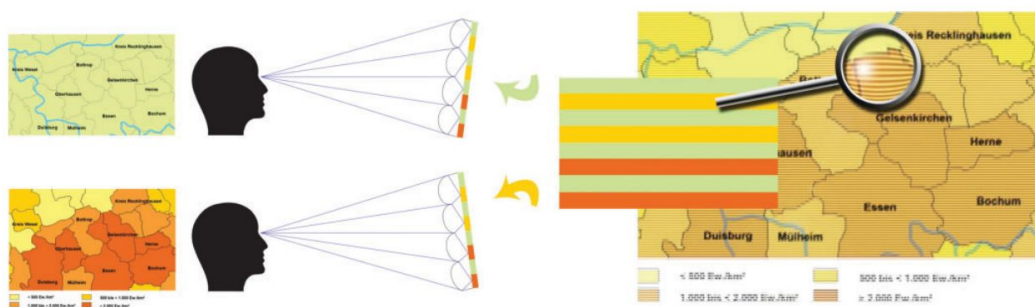


Figure 3.5.8: Functionality of the flip technique. When tilted vertically, different stripes of the map shift into the focus of the half-lenses. Source: Dickmann (2010).

We focus here on the creation of 2D effects through tilting movements. The simplest way to achieve this effect is by flipping lenticular cards, which

technique works with sets of at least two images. Figure 3.5.8 depicts the mechanics of this technique, which shows one image or the other according to the tilting degree of the map. One can use several images to increase the amount of information layers, which makes it suitable for comparing time-cuts of the spatial development of a region (Dickmann, 2010). We replaced the cards by a tablet, with smooth tilting movements to create twenty-four angles corresponding to each time unit, while being careful to avoid blindness caused by light reflection on the device's screen.

We support the efficacy of our technique on the use of kinesthesia, which enables humans to be aware of the position and movements of parts of our body by means of sensory organs (proprioceptors) in the muscles and joints, without relying on information from the five senses. Through kinesthesia, we are able to tell where different parts of our body are located even if they are not visible to our eyes. Since the kinesthetic experience can be more or less conscious, our acting in the world is constantly mediated by our “motor memory”, which comprises motor skills and the kinesthetic memory of performing them (Merleau-Ponty, 1996). Therefore, kinesthetic interaction technologies enable to directly address the bodily potential in interactive systems, leveraging the body's awareness and the perception of movements to enhance, utilize or develop one's motor skills (Fogtmann et al., 2008).

Kinesthesia has shown advantages in virtual reality applications, where it assists users to spatially orientate themselves inside virtual environments (Maciel et al., 2010), and improves object manipulation, which presents better performance when supported by a handheld device guiding the user from the physical space (Mine et al., 1997). Using tangible user interfaces reduces cognitive workload, while physical mobility may increase user creativity, which suggests that less constrained interaction styles are likely to improve users ability to think and communicate, while leveraging embodied cognition (Klemmer et al., 2006). The latter assumes that one's cognition is strongly influenced by aspects of one's body beyond the brain itself (Wilson and Foglia, 2017). Arvola and Holm (2014) showed that device-orientation based panning on hand-held devices is useful when engagement is considered important, which strengthen the idea that more intensive bodily interaction can be more engaging. Besançon et al. (2017) explore the possibility of using both tactile and tangible input for fluid dynamics data visualization using a portable, position-aware device, which was better appreciated by the users than a traditional mouse-and-keyboard setup.

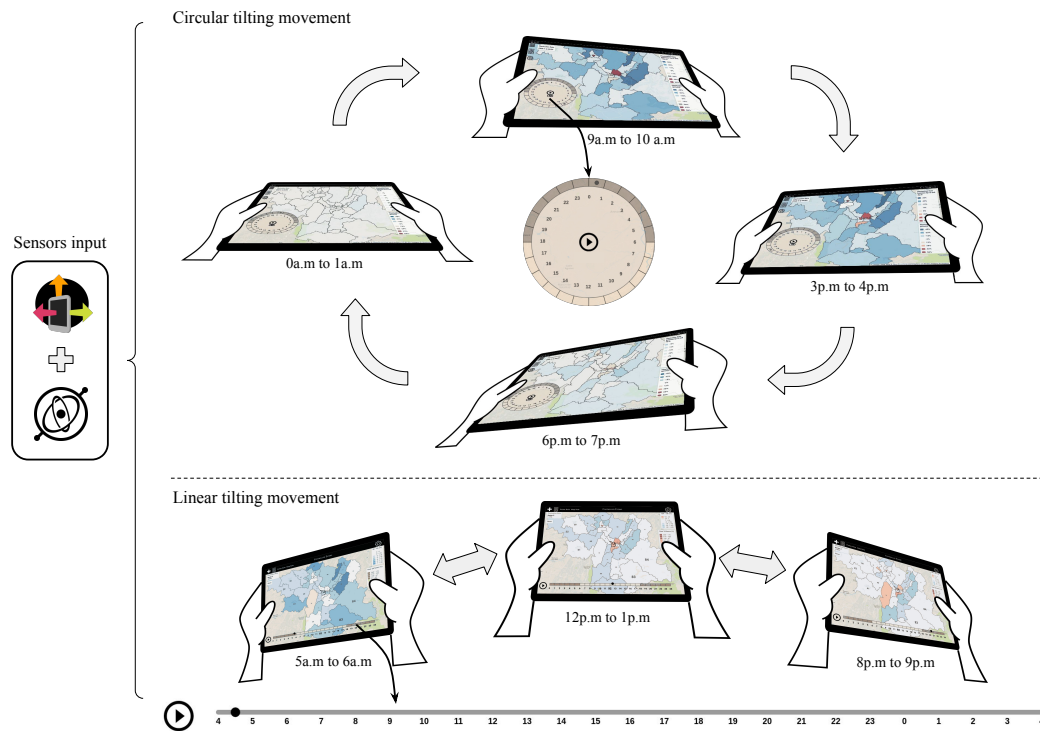


Figure 3.5.9: The interactive styles of *TiltMap* implemented on the basis of accelerator and gyroscopes inputs. Following the assumption that mobility patterns repeat themselves daily, we use a circular tilting movement to control time through a timewheel representation (top). We also provide a linear tilting movement to control time, due to the fewer degrees of freedom this movement requires compared to the circular one, and the familiarity of users to timelines (bottom).

Implementation We used a combination of accelerators and gyroscope input sensors embedded in the tablet to determine the inclination angle, which is mapped to one of the twenty-four time units on the time picker. Following the assumption that human mobility patterns repeat themselves daily (at least during weekdays), we provide a time picker in the shape of a timewheel, which is controlled by tilting the tablet in a circular way (Figure 3.5.9 – top). Nonetheless, our prospect users are well accustomed to timelines, which corresponding tilting movement leverage fewer degrees of freedom than the circular one. Therefore, the technique can be used to control time either through a circular movement or a linear one, tilting the tablet from left to right and contrariwise (Figure 3.5.9 – bottom). The latter is, however, limited by not providing continuity to represent the repetitive property of patterns, since

one should incline the device back to return on a certain time unit, instead of keep performing the movement as for the timewheel.

3.5.3 Interactive Exploration

Like most visual analytical systems, our visualization approach follows the visual information seeking mantra – *overview first, zoom and filter, then details-on-demand* – proposed by Shneiderman (1996), who defines a set of interactive tasks to support information visualization, which include:

- *Overview*: gain overview of the entire collection;
- *Zoom*: zoom on items of interest;
- *Filter*: filter out uninteresting items;
- *Details-on-demand*: select an item or groups and get details when needed;
- *Relate*: view relationships among items;
- *History*: keep a history of actions to support undo, replay, and progressive refinement; and
- *Extract*: allow extraction of sub-collections and of the query parameters.

As mentioned earlier, our system comprises multiple displays, each one embedding an *analytical dashboard* that can hold up to four multiple views (see Figure 3.5.10). Further, we extended our TiltingMap interface into a *control unit* that provides interaction with visualizations displayed over every dashboard using tactile and tangible input. The control unit displays the map view or the STC upon choice, which displays data information and supports tactile input to interact with other maps and charts on the dashboards. Each control unit comprises four interchangeable interactive interfaces, defined as follows:

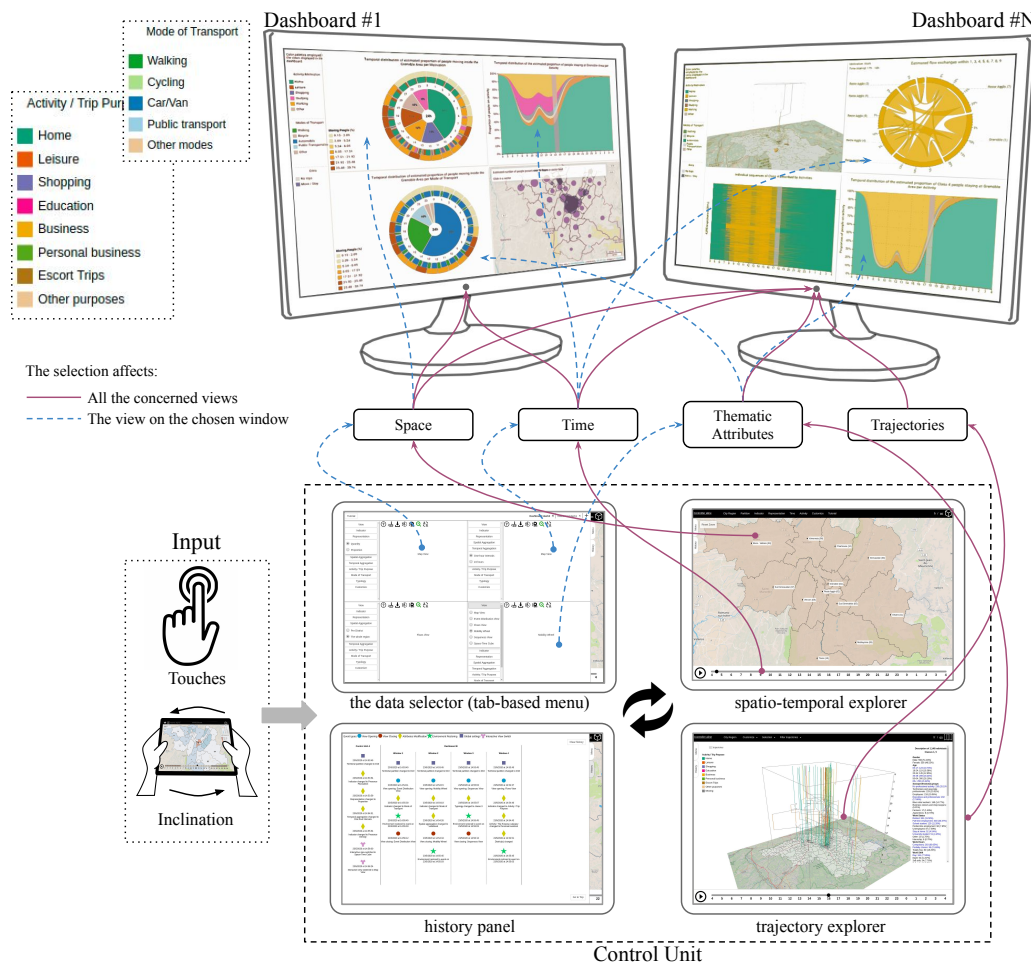


Figure 3.5.10: The overall structure of eSTIME’s interactive visualization. A mobile device serves as a control unit for interacting with analytical dashboards through four interchangeable interfaces: the *data selector* for opening, closing and modifying indicators; the *spatio-temporal explorer* for querying indicators over different spatial locations and time units; the *trajectory explorer* for visualizing and exploring daily trajectories; and the *history panel* that records user activity.

- the **data selector**, which exists in two formats:
 - a *tab-based menu*, where tabs comprise four “windows” (such as the dashboard interface) for directly managing the visualization and indicators on the connected dashboards. These windows contain each a dropdown-based menu to display and modify indicators, and a set of widgets to interact with the current displayed visualization (Figure 3.5.11); and

- a *navigation bar* manages the visualizations and indicators on the control unit interface (i.e. the map and the STC), and the selection of datasets and territorial partitions. The modifications regarding the latter two affect all displays, which means that it restores the visualizations previously opened with the selected dataset and/or territorial partition, while removing the ones that do not match the selection.

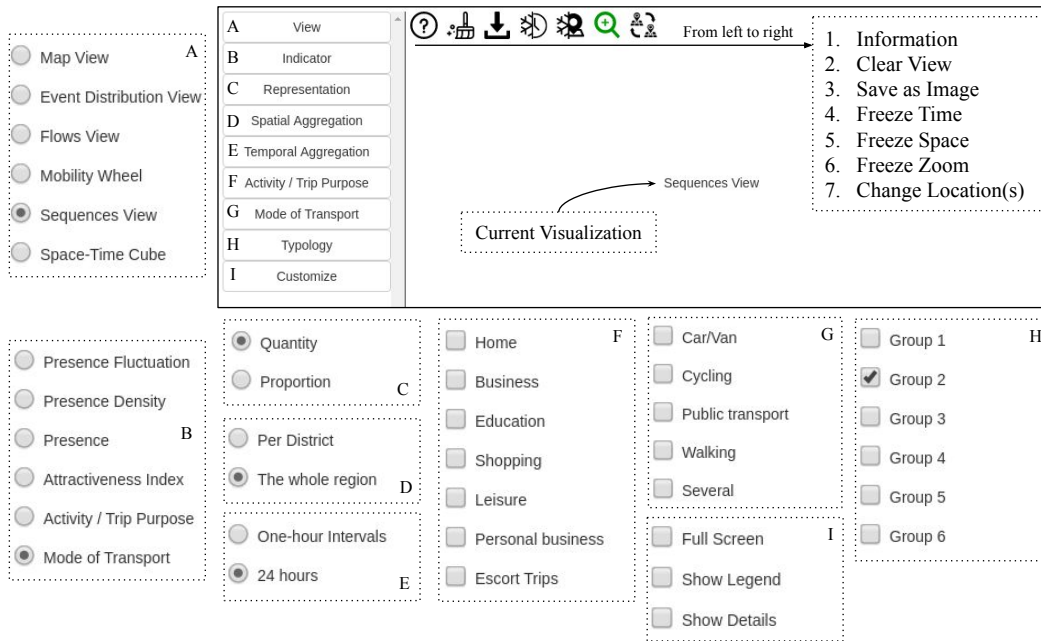


Figure 3.5.11: The layout of each tab in the *tab-based menu* supports four windows, each one comprising a dropdown-based menu (A-I) for building and visualizing indicators, and a set of widgets (1-6) to interact with the current visualization on that window.

- the **spatio-temporal explorer**, which serve as support to build and interact with indicators, changing them according to different districts and time units, or activating the details-on-demand functionality. A map provides the geographical information and an interactive timeline displays time as hours from 4am (the day before) to 4am (the survey day), which serves as a support for time unit selection by means of animation (see Subsection 3.5.2) or direct touch;
- the **trajectory explorer**, which comprises the STC and serves as visualization and exploration of daily trajectories. It is synchronized with sequences index plot to simultaneously analyze the shape and extent of trajectories and the temporal order of events; and

- the **history panel**, which keeps a record of the user activity within the environment, and can be used to undo/redo actions and to further understand the analyst's reasoning by reviewing their usage of the system (see Subsection 3.5.4).

A complete setup of our visualization interface requires a Control Unit and at least one dashboard, which synchronization is handled by a WebSocket-based server (see Subsection 3.5.5 for more details). The interaction happens through a one-to-many relationship from the control unit towards the dashboards (Figure 3.5.10). In a simple setup, the Control Unit could be used stand-alone, in which case the user would be able to explore indicators of presence dynamics and daily trajectories. In order to visualize and explore the remaining indicators, one must add at least one analytical dashboard by instantiating the application in a conventional display and associating it to the control unit by opening a new tab on the *tab-based menu*.

The user interaction follows the activity diagram depicted in Figure 3.5.12, which is defined to each sub-menu in the control unit. The activity flow starts upon a user input and finishes once the system made the action triggered by the input. Most actions are only applied to a chosen window, such as open a view, modifying the displayed indicator, and downloading the visualization as image (Figure 3.5.12 – green boxes). However, a few actions affect the whole environment (i.e. every associated dashboard and the control unit itself), such as changing the dataset and territorial partition, undo/redo actions, and selection operations of spatial locations, time units and trajectories (Figure 3.5.12 – yellow boxes).

Further to the action being local or global, it has two types: (1) the ones that users can apply at any moment regardless whether a visualization is being displayed or not, and (2) the ones that can only be applied to a visualization. Regarding the first type of action, one can use an event from the history panel for restoring the visualizations previously displayed on every or a particular dashboard, and change the dataset and territorial partition with which they want to work. Finally, they may display a visualization from the navigation bar or one of the dropdown-based menus on the tab-based menu.

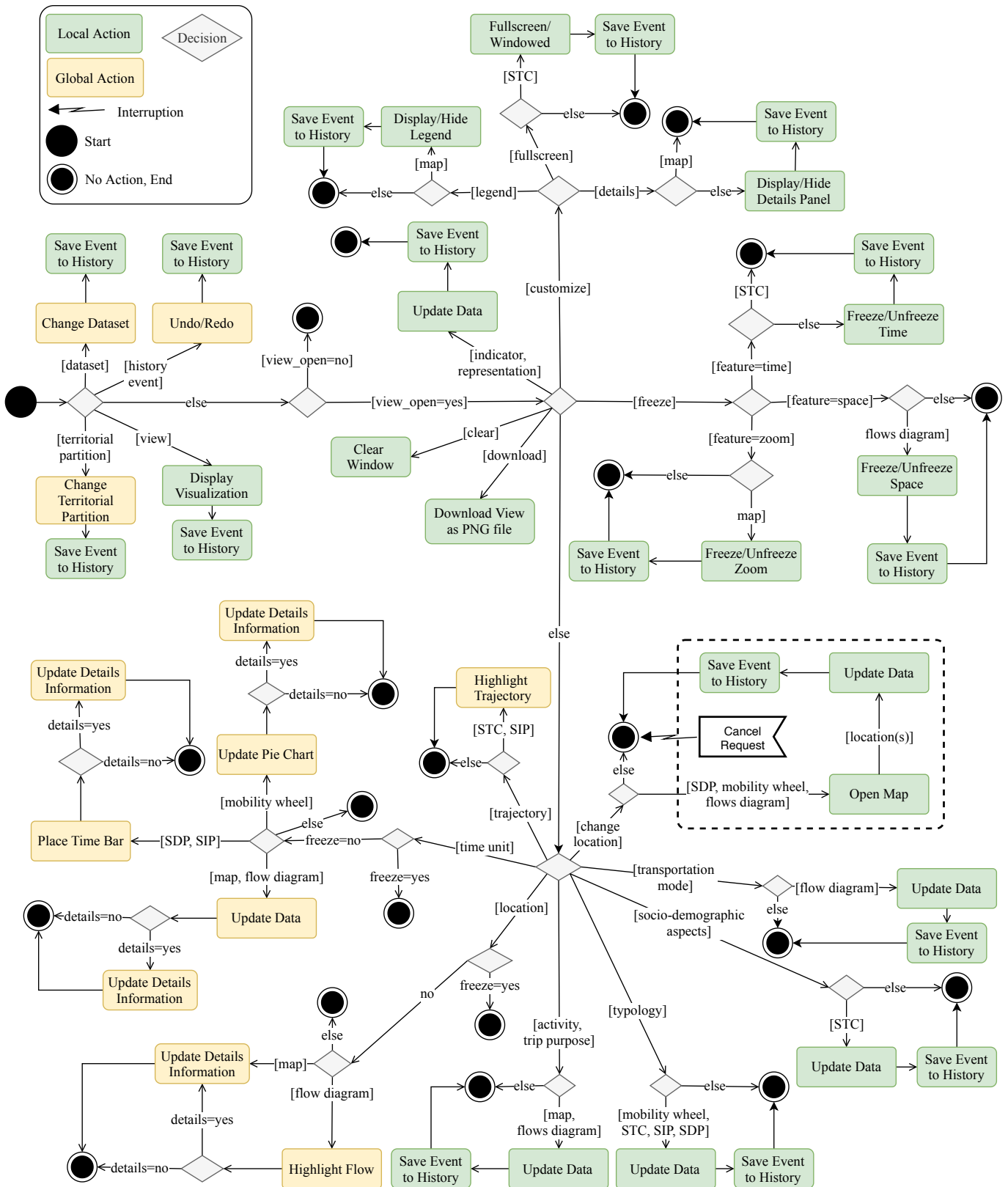
The map view can represent a variety of indicators describing the presence and absence of movers over the territory, while the remaining views represent only a particular indicator. Therefore, upon a view selection (Figure 3.5.11A), the default behavior of the system is to display either an empty map or the

corresponding indicator aggregate on time, space and/or thematic dimensions. A second step is required for the map view, where the user selects one of the following indicators: presence of movers, fluctuation, density or attractiveness (Figure 3.5.11B), which data is by default aggregate over 24 hours. Regardless the visualization, upon an indicator selection the system replaces the displayed data by the one corresponding to the indicator. For maps, the same behavior is expected upon the selection of a different representation of data (i.e. quantity or ratio).

The user may also freeze the spatial or temporal dimensions of one or multiple views (Figure 3.5.11 – 4-5), while the others preserve spatio-temporal animation. This approach enables comparison of indicators through time juxtaposing, which allows one to display side-by-side multiple versions of an indicator for different time units and/or locations.

The preselected values for spatio-temporal aggregation and thematic information of every indicator can be modified at any time, which triggers a filtering action. Upon a time unit selection, via direct touch or animation, the data and details-on-demand of every view are updated accordingly: if the temporal dimension is not frozen, the system replaces the data on maps, flows diagrams and the pie chart of mobility wheels, and place the time bar over the referred time unit on state distribution and sequences index plots. Picking a location on the map reveals the actual value of the indicator displayed on a map view, and highlight the ribbons connected to that location on flows diagrams when the spatial dimension is not frozen, while also presenting detailed information on flows exchanges when the details panel is enabled (Figure 3.5.11I). The “change location” widget (Figure 3.5.11 – 7) allows one to modify the spatial location(s) for which the indicator was initially built without changing spatio-temporal aggregation and thematic attributes already displayed. Upon tapping the widget, the system shows the map where the user may choose the new location(s) or cancel the action. The former will update the data on the visualization accordingly. The spatio-temporal interaction through the map and timeline modifies all the indicators on every connected dashboard, while using the widget requires one to choose a specific dashboard and window, where the indicator should be modified.

Finally, since producing reports is a standard practice within exploratory analysis, we provide two functionalities to enrich the report: a snapshot function to export the views as images (Figure 3.5.11 – 3) and a mechanism to display details on the data.



Obs.: SDP and SIP stand for State Distribution Plot and Sequences Index Plot, respectively.

Figure 3.5.12: Overview of eSTIME’s activity flow.

3.5.4 History of User Activity

Further to allowing undo, replay, and progressive refinement actions, keeping the interaction history of an user inside the visualization interface produces *provenance information*, which can help to describe the process of the analysis, revealing discovered insights and the users' reasoning that led to these insights (North et al., 2011). Xu et al. (2015) define provenance information via a four-level hierarchical model, where the bottom-level consists of low-level user interactions such as mouse clicks and keystrokes, which have little semantic meaning. The next level up consists of actions, which are analytical steps such as querying the database or changing the zooming level of a data visualization. Further up are the subtasks, which are the analyses required to reach the sense-making goal, which in our case refer to the user queries applied to indicators. The top level shows the task – the overall sense-making undertaking – which in our case is “analyze daily urban mobility”.

Our framework provides a exploratory visual analysis of multidimensional data describing daily urban mobility, which combined with our interactive approach allow users to produce diverse analysis workflows that allow to answer the same sense-making question, but also enable many other discoveries in the process. For instance, understanding whether users explore the temporal variation of an indicator using animation or juxtaposing and how this technical choice may or may not affect the outcomes could be relevant to improve and even to propose appropriate workflows of analysis.

Although we could not address analytic provenance in the context of this thesis, we did provide a history panel (Figure 3.5.13) within our visualization interface that record relevant actions to understand the reasoning of analysts in a further study. The recorded actions are defined as follows:

- *view opening/closing*;
- *attributes modification*, which describes a change of indicator, thematic and spatial data, displaying/hiding details and filtering by typology's group;
- *environment restoring*, which refers to undo/redo operations through an episode, by restoring a dashboard or the entire environment, i.e. affecting the control unit and every connected dashboard, to the event's date;

- *global settings*, which describes changes that affect the entire environment, such as changing the territorial partition or the data set;
- *interactive view switching*, which refers to the action of switching between map and STC on the control unit interface.

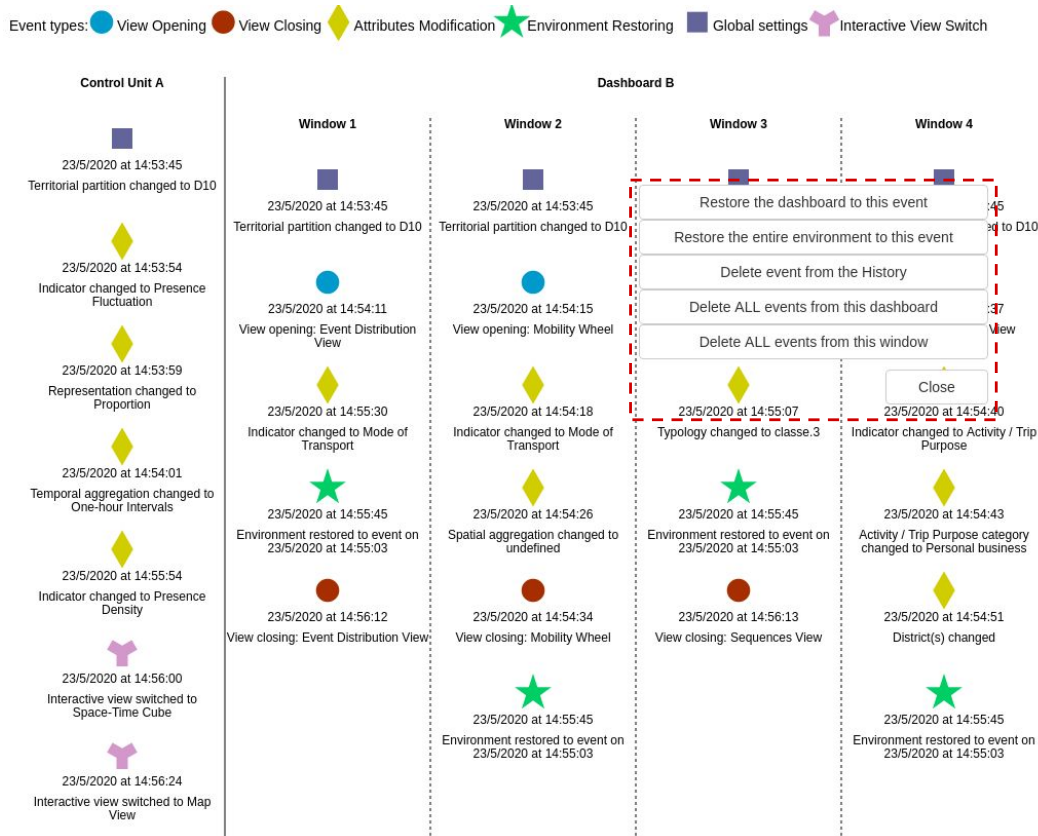


Figure 3.5.13: The *history panel* of control unit *A*, which dashboard *B* is associated with. Each window has its own history, which records actions of opening/closing a view, attributes modification, environment restoring, global settings and interactive view switching. A menu is available over each episode (red dashed rectangle), allowing the user to restore the dashboard or entire environment to the time of that event, or to delete that event or all events from the corresponding window or dashboard from history.

Each historical episode contains the date and time when it happened, a symbol representing the type of action, and information of currently displayed elements in every dashboard. Each analytical dashboard and window has its own history, which records actions of opening/closing a view, attributes modification, environment restoring, global settings and interactive view switching.

A menu is available over each episode (red dashed rectangle), allowing the user to restore the dashboard or entire environment to the time of that event, or delete that event or all events from the corresponding window or dashboard from history. Up to this date, this information is used for undo/redo actions and for recovering the visualization setup on a later date. However, further analysis on the collected data could easily allow one to understand the analyst reasoning through the collected information, since we can know exactly where and when a visualization was opened, closed, modified, and the modification types.

3.5.5 Technical Aspects

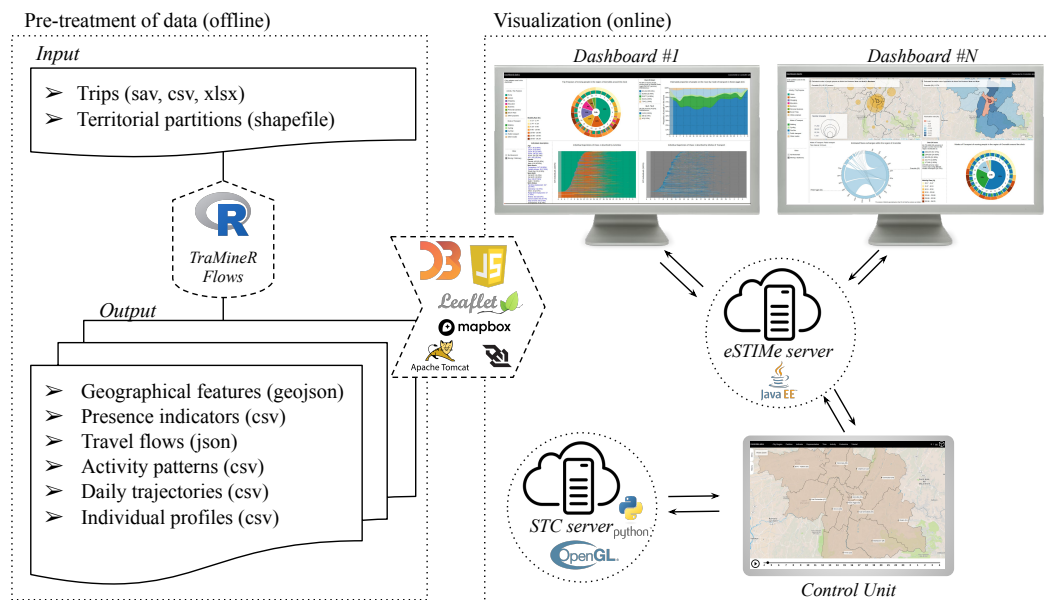


Figure 3.5.14: The working flow of eSTIME. Firstly, the data goes through a cleaning and statistical treatment to calculate the mobility indicators. Secondly, the output data are visualized through Web-based technologies. The application can be instantiated multiple times simultaneously, with each setup comprising a control unit and at least one dashboard, which communication is managed by a central Websocket server. The control unit communicates yet with a second server, which provides and manages the space-time cube.

Figure 3.5.14 presents the working flow of eSTIME, which has two phases: data treatment and visualization. The former is performed using the free R statistical and graphical environment (R Development Core Team et al., 2011).

Further to the functionalities provided by the Tidyverse package (Wickham, 2017) for manipulating data, we particularly use the Flows (Giraud and Beau-guitte, 2016) and TraMineR (Gabadinho et al., 2011) packages to, respectively, extract the matrices of flows and the typology of activity patterns. The input of our scripts are the raw data from each survey, which might take different file formats (e.g. sav, xlsx, shapefile), describing the individual trips and the different territorial partitions provided in the data. We locally store the output data as *geojson* files for geographical features, *json* for flows data, and *csv* for the remaining.

The visualization is almost completely developed on the basis of web technologies (i.e. Javascript), except for the STC, which uses Python and the OpenGL library for rendering the 3D image. We use D3 (Data-Driven Documents) and Leaflet libraries to generate charts and cartographic representations, respectively. The map tiles are provided by the Mapbox Styles API ¹⁰.

Although eSTIME can be launched standalone on the tablet, where the user can explore presence dynamics indicators and daily trajectories, a complete setup consists of a control unit and at least one dashboard. A central server (i.e. eSTIME server) implemented in Java and handled by the Apache Tomcat software, a free and open-source cross-platform Web server software¹¹, manages the communication between a control unit and its associated dashboards. Further, the control unit communicates with another server (i.e. STC server) implemented in Python using the *gevent-websocket* project¹², which provides and manages the STC visualization.

The current version of our prototype enables one to instantiate eSTIME several times simultaneously. However, the exploration of daily trajectories is limited due to the STC being only available for one of them at the time. eSTIME can be used independently of the STC, which only limitation is that one would not be able to visualize daily trajectories in space and time, but rather to explore them through the sequences index plot.

¹⁰<https://docs.mapbox.com/api/maps/#styles>

¹¹<https://tomcat.apache.org/>

¹²<https://pypi.org/project/gevent-websocket/>

3.6 Use Case Scenarios

To demonstrate the usage of our visual and interactive tools, we describe the mobility and presence patterns of people within the great regions surrounding different metropolitan areas to understand the relationship between the metropolis and its adjacent territories. At the time of this thesis, we did not have access to a coarser spatial granularity than polling districts where to represent the dataset of Rennes region, which territorial partition would ease the exploration of such relationship by highlighting the metropolitan territory. Therefore, the scenarios hereafter are built through the exploration of Lyon and Grenoble's datasets which derived indicators are described over a spatial granularity of intermediate and large areas. Both metropolitan areas are located in the same region of France, *Auvergne-Rhône-Alpes*. Lyon is the regional capital and the second biggest metropolis after Paris, which surveyed territory has a population of around 2.2 million people. Grenoble is located at the French Alps' foot and is an important European scientific center, which surveyed territory includes a great mountain area and has a population of around 800,000 people.

3.6.1 Scenario 1: The reasons driving human mobility

This scenario investigates the reasons that drive the daily mobility of people within the urban area of Grenoble. The studied territory is particularly shaped, with great part of towns and villages located on the mountains. Thereby, we start the analysis by looking at the attractiveness indices of districts in the set of intermediate areas (Fig. 3.6.1a), which territorial partition allows to identify attractive locations within the metropolis. As expected, we notice that the two greatest agglomerations in the territory, i.e. *Voiron* and *Grenoble*, have a capacity to accommodate along the day an amount of people that is almost twice their population size. Within the metropolitan area, we spot three strongly attractive locations: Grenoble's city center; the area around *Meylan*, where a science park is installed; and the University campus area, which draws in about 250% more people than its population from 8am to 4pm.

We pursue the analysis using a coarse spatial granularity, which represents the region's inter-municipalities, and can therefore help us to understand the relationship between suburban locations and the metropolitan area. In this

territorial partition, the Metropolis area (as defined at the time of the survey) is centralized in the map, partitioned as: *Grenoble* – the metropolis heart – and *Reste Agglo*, which aggregate the remaining towns (Figure 3.6.1b – left). The average presence fluctuation indicates that every location in the region accommodate more people than their population over 24 hours. Nonetheless, the variation of this indicator over time shows that while the metropolitan area can be overpopulated by up to 11% at certain time units, the remaining locations remain constantly underpopulated. Particularly, we observe this phenomenon in the locations of *Sud Grésivaudan (SGres)* and *Sud Grenoblois (SGren)*, which over the day accumulate a number of people that is 8% and 39% above their population size, while hourly, they can have a number of people up to 13% and 24% lower of their population size, respectively. Figure 3.6.1b shows specific time slots chosen to represent the temporal variation of presence fluctuation across the territory, which shows a similar behavior in both locations. They are both located on the mountains, which make them geographically far away from each other in terms of daily migrations. They also differ in terms of distance to the Metropolis, with *SGres* located farther away than *SGren*. Thus we continue the analysis seeking to understand whether and why they depend on the metropolis.

The flow diagrams of *SGres* and *SGren* (Figure 3.6.1c) represent the aggregate count of trips over 24 hours for all purposes and transportation modes combined, which shows absence of movement between them along the day. Further, they are responsible for only a small part of trips among the locations with which they are linked (*SGres* generates 5% of flows – 140,000 trips, and *SGren* generates 4% – 108,000 trips). This small contribution might be a consequence of their relationship with the metropolitan area, which is responsible for the majority of travel flows within the whole region. Following a deeper exploration of both locations' travel patterns, we observe that trips concerning *SGres* are predominantly within the district (86.1%), and the few interterritorial relationships are mainly with neighboring locations. Regarding *SGren*, we notice that about half of trips are inner district (48.5%) and the remaining are mostly going to or coming from the metropolitan area (43%). These patterns do not vary much over time, which suggests that *SGren* is highly dependent of the Metropolis, while *SGres* seems to be self-sufficient.

Analogous to the pattern observed for the whole region, the mobility rate is roughly the same for *SGres* and *SGren*, where peaks of movement are observed in the morning (from 8am to 9am), midday (from 11am to 2pm) and evening (from 4pm to 7pm) periods, when up to 30% of people that travel inner or towards both locations are on a move (Figure 3.6.1d depicts this pattern within

SGren and *SGen*). In the morning, people travel mostly for business and education, which pattern repeats itself short after the lunch pause, around 1pm. We observe that near midday (from 11am to 12pm) people mostly travel home, where they supposedly have lunch. From 6pm people would start traveling home or for leisure activities, which last up to 10pm.

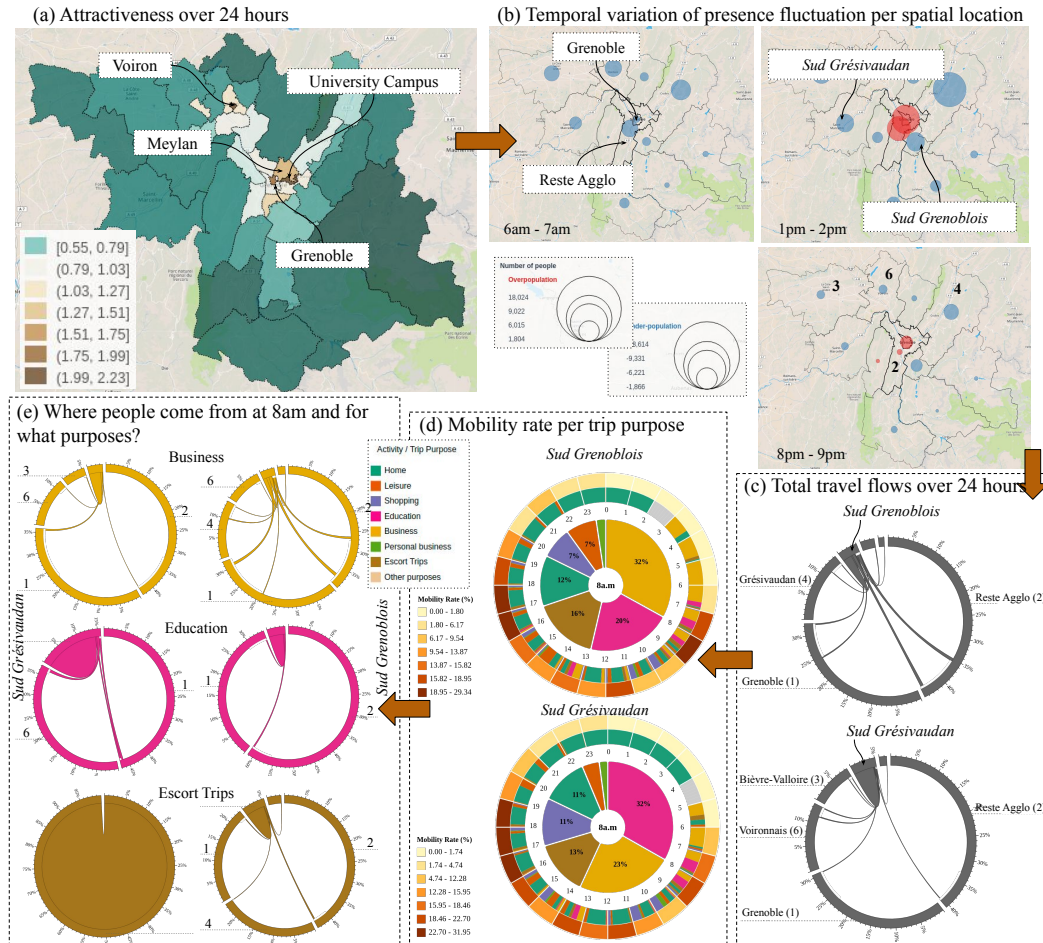


Figure 3.6.1: Scenario 1: Understanding the reasons that drive human mobility within the great region of Grenoble metropolitan area.

During the morning, the movement peak is slightly less intense in *SGres* than *SGen*, where the main reasons to travel are business and education, respectively (Figure 3.6.1d). The trips regarding education are mostly inner district, probably because the people concerned by these trips are children, which respective schools are normally within their neighborhood. There is about the same proportion of people traveling to escort someone in both districts, who, based in the previous assumption, could be the parents accompanying their children to school before going to work, since more than 25% of people per-

form various trips for different reasons. Lastly, we observe that *SGres* has no incoming trips during this period, suggesting that the 23% of people traveling there for work are actually residents moving inner district. The scenario is quite different regarding *SGren* (Figure 3.6.1e), where the 32% of people there for business during the morning generate about half of the trips concerning this location (54%). From these, about half are inner district (27%) and the other half come from other locations, particularly from the metropolitan area (19%).

3.6.2 Scenario 2: The reasons and transportation means underlying traveling patterns

This scenario focuses on the transportation modes that underlay the mobility patterns of the urban area of Lyon. We use the territorial partition into large areas, which attractiveness indices show without surprise that the most attractive district is the one where the airport is situated (Figure 3.6.2a). The heart of the metropolitan area, which comprises the cities of *Lyon* and *Villeurbanne*, and the commune of *Chaponost* are second placed with a slightly lower index. The latter is known for its Roman aqueducts, which may be appealing to tourists visiting the region.

The average presence fluctuation shows that these locations receive along the day a number of people that is 30 to 50 percent greater than their population size. Particularly, the airport area accommodate 50.6% more people than its population. However, similar to the urban area of Grenoble, every location receives in average more people than their population over the day, while remaining underpopulated throughout different time units (Figure 3.6.2b). Considering how the areas around *Chaponost* and the airport are attractive, it is curious to observe that they are constantly underpopulated at different hours of the day. From 8am to 5pm, the former accommodates a total number of people that is equivalent to maximum 75% of the population. The airport area is less visited in the afternoon, registering a number of people present that is equivalent to maximum 84% of the population size. Finally, although the urban core is overpopulated from 8am to 3pm, the number of visitors is at the most 7% higher than the population size.

Both locations, *Chaponost* and the airport area, do not exchange flows (Figure 3.6.2c), which is curious since the airport constitute an important transport facility for the entire *Auvergne-Rhône-Alpes* region. Further they

are responsible for only a small part of trips among the locations with which they are linked, which is likely because the major part of trips is from or towards the metropolitan area. The latter is responsible for around 34.6% of outgoing trips from *Chaponost* and 45.6% of incoming and outgoing flows of the airport area.

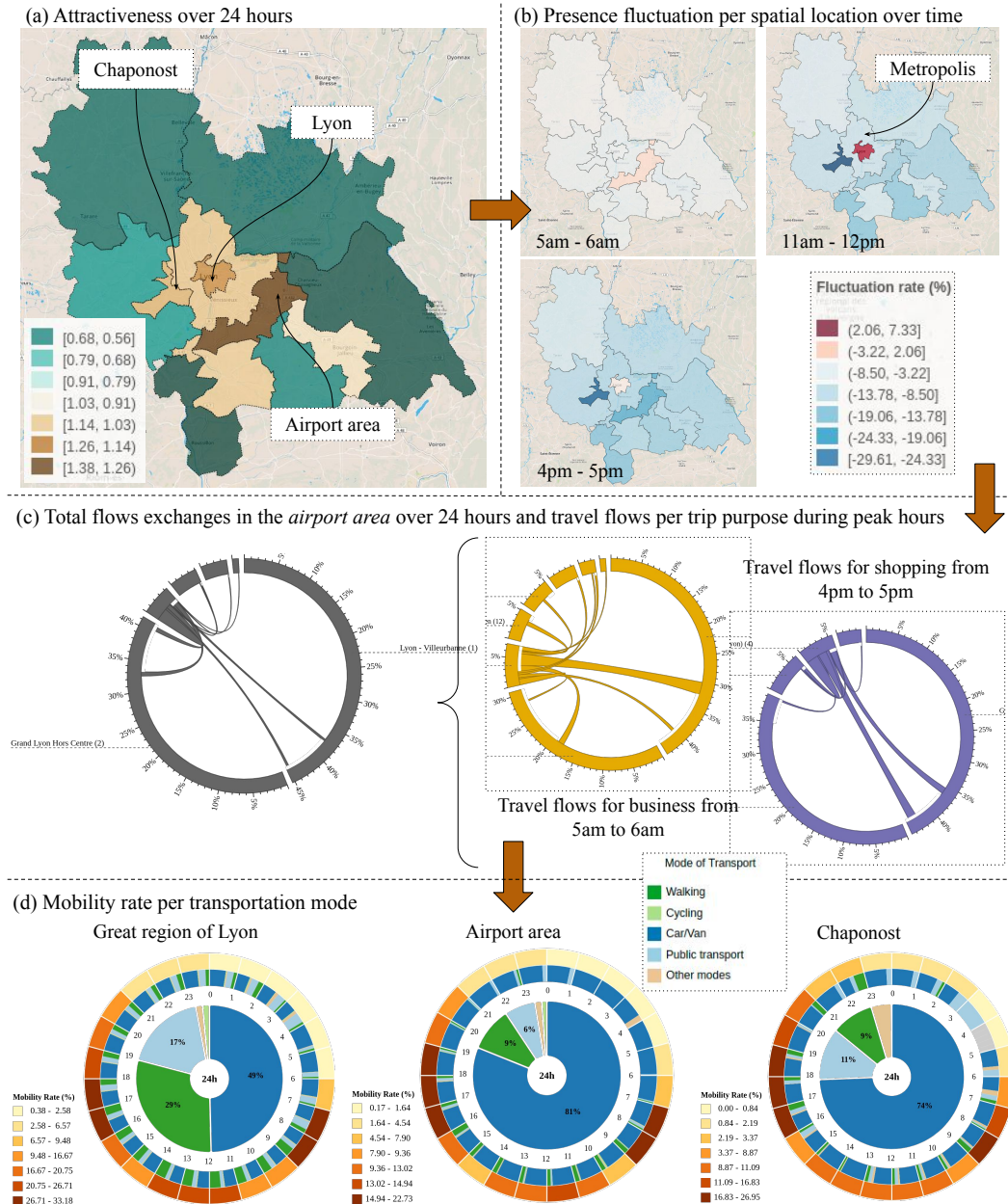


Figure 3.6.2: Scenario 2: The reasons and transportation means underlying traveling patterns within the great region of Lyon metropolitan area.

Although the airport area does not have a high mobility rate in the morning period from 5am to 6am (2.64%), this location seems overpopulated at this time, having the equivalent to 1.13% more people present than its population size. Our hypothesis is that the residents are still asleep while people are traveling towards the airport to catch a flight or to work. Therefore, we continue the analysis looking for understanding the reasons why people travel there during this period. At the early morning, only 17% of the flows are inside the district, while 64% are incoming flows from everywhere within the region, which main reason to travel is business-related. In the afternoon from 3pm to 4pm, when the location has the lowest proportion of people present with reference to the population (-16.67%), there are 44.5% of trips inside the district and 26% of outgoing trips are towards the metropolis and neighboring locations, predominantly for leisure and shopping, which 42% of outgoing trips are towards communes in the metropolitan area (excluding the urban core).

Considering the imposed schedule by society for business and education, the movement peak hours tend to be roughly the same across different territories, i.e. high mobility rate in the morning and evening, and moderate movement at noon (Figure 3.6.2d). The commune of *Chaponost* does not have a particular period of high mobility rate at midday, conversely to what we notice for the whole region and airport area. Despite the automobile being largely used throughout the whole region (49% of people), the population tend to travel quite as much by walking (29%) and public transportation (17%) combined. For the airport area and the commune of *Chaponost*, the automobile is predominantly employed for traveling inside or towards the district, being responsible for 76.2% and 67% of the trips generated by the airport area and *Chaponost*, respectively. The latter has around 5% more people traveling in by public transportation and walking than the airport area.

3.6.3 Scenario 3: The latent activity programs of daily mobility

As mentioned earlier, we performed a cluster analysis based on the Dynamic Hamming Distance method to extract groups of daily trajectories according to similar activity patterns of 14,821 individuals from the dataset of Grenoble and 25,202 from the dataset of Lyon. Therefore, this scenario discusses the typology of activity patterns resulting from these datasets, and highlights the similarities and differences between travel-activity patterns of both regions' populations.

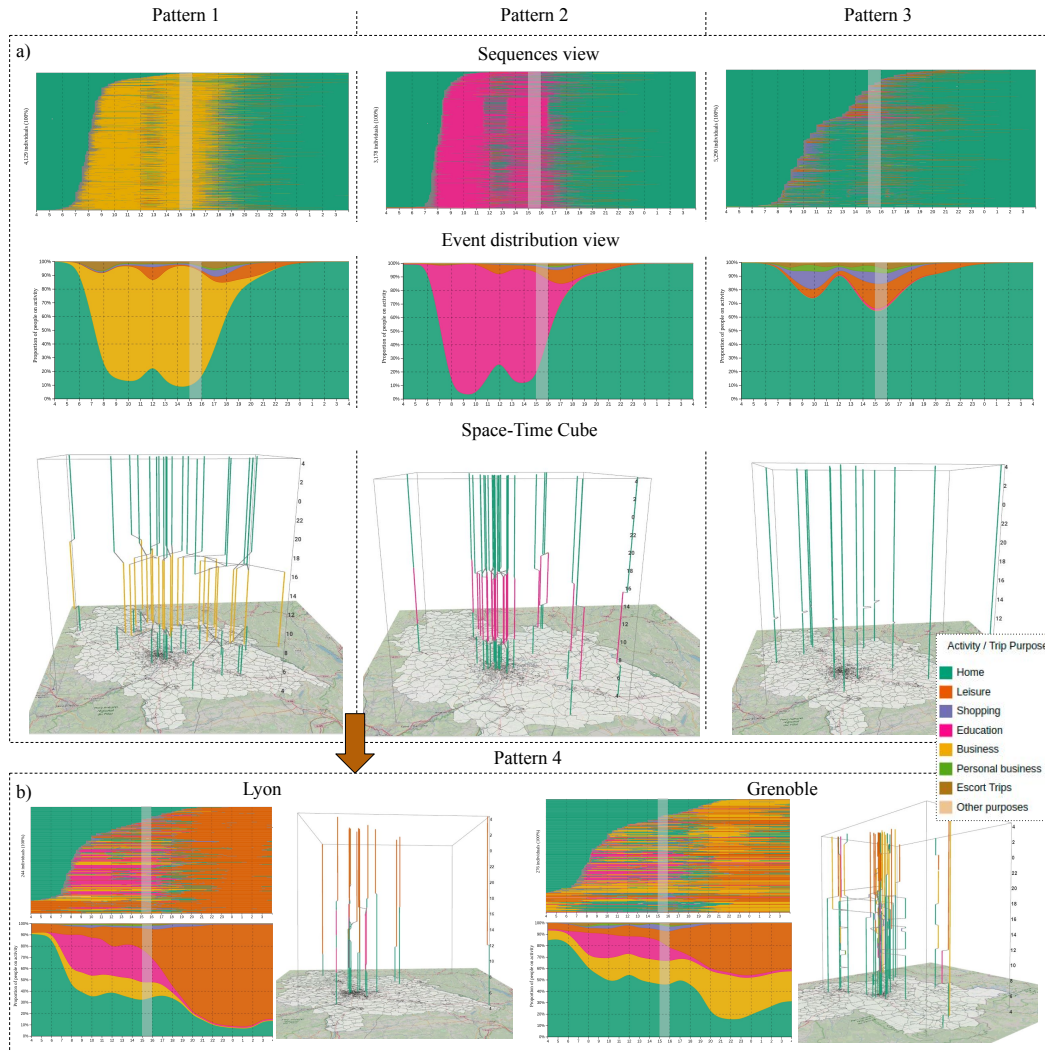


Figure 3.6.3: Scenario 3: The travel-activity patterns resulting from daily trajectories of individuals within the urban areas of Grenoble and Lyon.

The typology distinctly extracts three groups from both datasets: full-time employees, full-time students and stay-at-home people (Figure 3.6.3a – pattern 1). The group of individuals with a full-time employment represents 26% and 29% of people in Lyon and Grenoble, respectively. They work in average from 8am to 6pm, with varying arrival and departure times, ranging from 6am to 9am and 4pm to 7pm, respectively. During the lunch break – between 12pm and 2pm – the individuals who leave their workplace travel mostly home, where we assume they have lunch, or elsewhere to perform leisure activities. They are aged from 25 to 64 years, which most represented age range is 35 to 49 years old (43.6% of individuals).

The group of full-time students represent a similar part of individuals in both regions (around 22%). They seem to have a tight schedule, which arrival time at school (about 79% of individuals, aged from 5 to 17 years) or University (around 18%, aged from 18 to 25 years) would be the latest 8:30am. The event distribution chart for this group shows that the estimated proportion of people studying reduces from 97% in the morning to 80% in the afternoon, when people would go home or chain up leisure activities (Figure 3.6.3a – pattern 2). The third group represents people that tend to stay at home during the whole day, performing temporally sparse and short trips for leisure or shopping activities (Figure 3.6.3a – pattern 3). This group constitute 36% of the population in both regions, whom are mostly retired, aged 60 years or more.

The spatio-temporal visualization of representative patterns in each group (Figure 3.6.3a – bottom) shows that people would travel longer distances for business than education purposes. According to the previous scenarios, this spatial pattern is expected, since the suburban population would likely move towards the metropolitan area for work, resulting in longer trips, while the majority of individuals in the students class are minors, which means they attend elementary, middle or high schools located in their respective neighborhoods. Further, the space-time paths of individuals in *pattern 3* resembles straight vertical lines, indicating that their trips are not only short in time, but also in distance.

These are nonetheless expected patterns considering that most people are usually employed, studying or retired. We discuss now the profile and traveling patterns of individuals that compose a group of “atypical” daily trajectories in both regions. They present a similar pattern in terms of the time they leave and return home, yet different activities are performed outside their residence location. These people would spend their daily time either at home or studying, and the evening and night time would be predominantly dedicated to leisure in Lyon, while in Grenoble the individuals are evenly split between business and leisure activities (Figure 3.6.3b). Such activity pattern can be explained by individuals profile, whom are mostly students (52%) and retired people (17%) in Lyon, while in Grenoble, there are more individuals in a full-time employment (53%) and only 27% of students.

3.7 Summary

In this chapter, we presented the visualization framework we propose to assist the visual analysis of urban mobility data. Since we focus on daily movement patterns, we use data from a household travel survey, which records individual trips of a population over 24 hours, from 4am (the day before) to 4am (the survey day) within an urban area. The trips are semantically enriched with information on travel's purposes and transportation modes. Further, the data describes people through information such as age, gender, occupation, socio-professional category, and place of residence. Thereby, the data allow to address the daily urban mobility phenomenon through the analysis of the variation of indicators derived from three objects of interest:

- the *travel flows and trips*, which reveals the urban structure through the aggregation of trips between pairs of locations at different time units;
- the *territory and population* dynamics, which address the variation of presence and absence of people in different locations over time; and
- the *daily trajectories*, which are defined as the space-time path (i.e. the sequence of activities and trips) of an individual along the day, and allows to understand how the individuals schedule their activities over time according to the spatial context of the territory.

To enable these analyses, we followed a four-step workflow (Figure 3.7.1). Firstly, we prepared the raw data to enable the extraction of information matrices of flows, presence and sequences. Secondly, we used these matrices to derive a set of indicators that describe our objects of interest from various spatio-temporal granularity levels and thematic attributes. Thirdly, we proposed a system of tasks based on the framework of [Andrienko et al. \(2011\)](#) to guide the querying of indicators over the Cartesian product of four dimensions $S \times T \times O \times A$. The proposed questions can be synoptic, targeting the whole set of reference (e.g. all spatial locations or time units), or elementary, targeting only one element (e.g. how are the flow exchanges between a pair of locations at a particular time unit). The system is generic enough to target any subset of locations, time units, objects, and thematic attributes. However, the current prototype supports only the querying of indicators over predefined spatio-temporal aggregation and thematic categories.

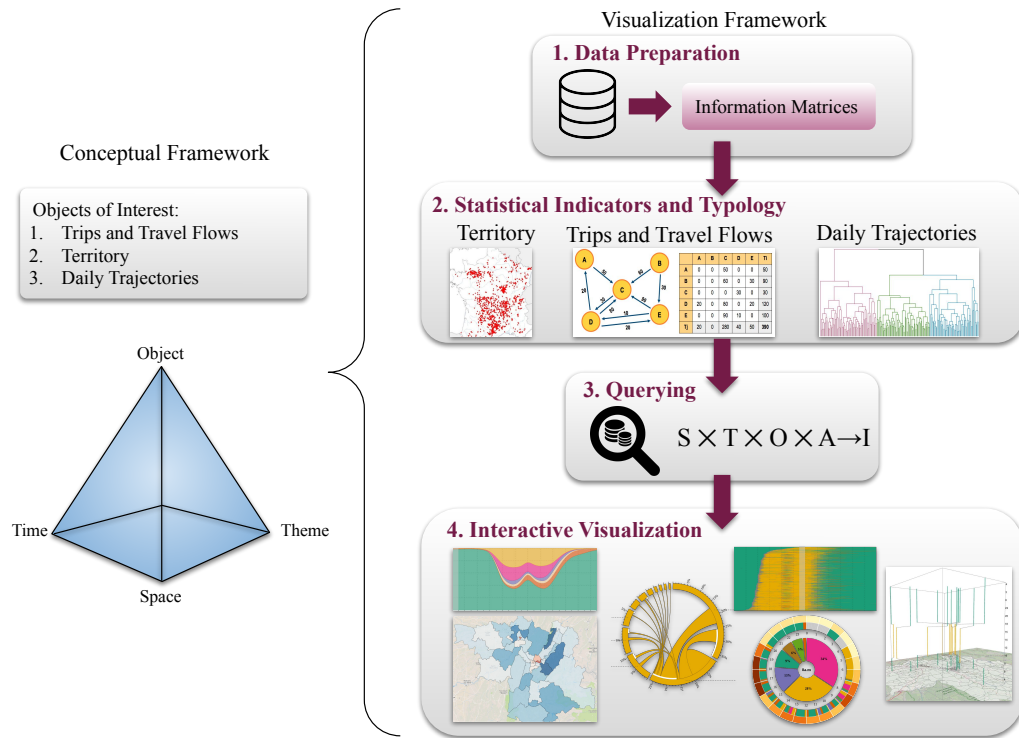


Figure 3.7.1: The four-step workflow followed to conceive the eSTIME visualization framework.

Finally, we provided a visualization interface that assist the querying of data through interactive maps and charts to support the representation of indicators derived from our three objects of interest (Table 3.7.1) and their exploration via multiple spatio-temporal granularity levels and thematic attributes. Our system was designed to assist analysts who are not necessarily transportation experts, which means they might not have the necessary knowledge to extract indicators from the data, but they need the information to support decision-making in urban planning, transportation offers, catastrophe or epidemics management, and so on. Therefore, eSTIME's interface is flexible, customizable to allow the analyst to visualize any indicator that is considered appropriate to the ongoing analysis, while exploring them over different spatio-temporal granularity levels, and comparing them side-by-side or through animation to reveal their variation over time.

The system can manage multiple displays, which provide as much space as needed to thoroughly explore the data. Further, the system adapts itself to different technological setups, e.g., one can use the control unit on a conventional display, when a tablet is not available, using mouse and key-

<i>Object of Interest</i>	<i>Indicator</i>	<i>Visualization</i>
Travel Flows and Trips	Travel flows (per mode / purpose)	Flow Diagram
	Mobility Rate	Mobility Wheel; State Distribution Plot
	Attribute Share	Mobility Wheel; State Distribution Plot
Territory	Presence (total / per activity)	Choropleth and Proportional Symbols Maps; State Distribution Plot
	Presence Density	Choropleth map
	Presence Fluctuation	Choropleth and Proportional Symbols Maps
	Attractiveness	Choropleth map
Daily Trajectories	Typology of Activity Patterns	Sequence Index Plot; Space-Time Cube

Table 3.7.1: Summary of visual representations proposed for exploring the statistical indicators and the typology of activity patterns.

board input instead of touches. These modifications remove the possibility of animating time through the inclination of a device, but comparison is still possible through time juxtaposing and the direct selection of time units on the timeline.

To demonstrate the usage of our visualization and interaction tools to execute the different types of analysis through our system of tasks, we presented three use case scenarios that reveal the territorial dynamics of two metropolitan areas in France, which differ in terms of geographical and economical aspects. These scenarios allow us to establish the complementarity of indicators, maps and charts on the discovery of new patterns or simply to highlight well-known behaviors of a population.

Furthermore, we could demonstrate that our framework is generic enough to enable the analysis of daily mobility data from different urban areas. Although the data source is standardized, the datasets originate from different survey formats, which implies some differences on how the data is collected and structured (e.g., in the Grenoble dataset, arrival and departure time are

stored as separated columns for hours and minutes, while for the other two this information is concatenated into a single column per time). These small modifications allowed us to establish a script of data treating that is generic enough to process any HTS type of data.

The remaining of this thesis will focus on the user evaluations performed to assess the usability and suitability of our framework. Four user experiments were conducted with people of different profiles, such as age, gender, and expertise level regarding human mobility. Furthermore, we performed several demonstrations of eSTIME to professionals on the domain, which allowed us to better understand their needs, and the advantages and drawbacks of our proposition according to the required cognitive effort, preferences or limitations of analysts' everyday work.

User Evaluation

4.1 Introduction

The conception of our visualization interface was accompanied by a researcher¹ with substantial knowledge on the domain of human mobility, and followed an interactive cycle in five-steps (Figure 4.1.1), defined as follows:

1. the *implementation* step consists on developing a first prototype that embeds the main visual and interaction tools, i.e. multiple synchronized displays, and tactile and tangible interaction through a mobile device. Particularly, the outcome of this step was *eSTIME 1.0*, which enable the exploration of urban mobility data through indicators of travel flows, presence density and fluctuation, attractiveness, mobility rate and attribute share (i.e. transportation mode).
2. the *user evaluation* step consists on evaluating the usability of our visual and interaction tools through user participation. Particularly, we performed four user evaluations, three of them followed a quasi-experiment design without control groups, which aimed to evaluate the interface as a whole, and one evaluation followed a formal experiment design to compare the usability and suitability of our movement-based interaction interface against traditional time animation methods.
3. the *statistical analysis* step processes the empirical data resulting of these evaluations in order to accept or refuse the hypotheses that drove each evaluation.
4. the *hypotheses assessment* step uses the outcomes of the statistical analysis and user feedback collected during the previous evaluation to accept or refuse the hypotheses.

¹Sonia Chardonnel, a researcher fellow at CNRS (*Centre National de la Recherche Scientifique*, in French)

5. the *refinement* step improve the visual and interaction tools of the prototype according to the previous experiment outcomes. Particularly, this step was performed three times, twice to improve the whole interface resulting on two other prototypes: *eSTIME 2.0* and *eSTIME 3.0*, the latter being the current version of our visualization interface.

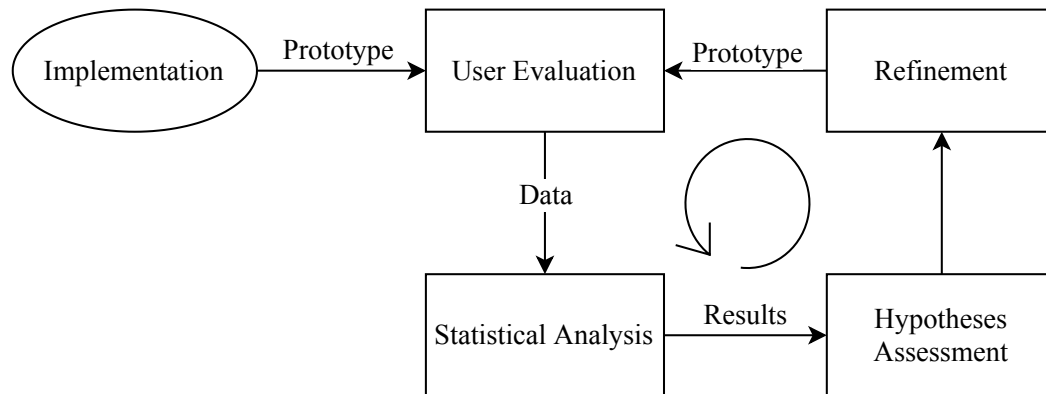


Figure 4.1.1: The eSTIME implementation cycle. Several user evaluations were performed to progressively improve our prototype.

As mentioned earlier, it is difficult to get access to a group of experts on the domain, specially to take part in a iterative evaluation process, which requires a long term involvement. Therefore, we invited people from diverse backgrounds to evaluate different aspects of the visualization. Overall, mainly three types of users took part in our experiments, defined as follows:

- *non-experts* on the domain, which were mainly researchers on computer science-related disciplines;
- *trainees*, which correspond to a group of people (students) involved on disciplines of geography that address in-depth the subject of human mobility; and
- *experts*, which correspond to a group of people with substantial knowledge on the domain, working with human mobility data for many years and on a daily basis.

The remaining of this chapter is organized as follows. Section 4.2 presents the mutual material and methods to all user experiments. Section 4.3 describes a first experiment performed with non-experts to evaluate the usability of

eSTIME 1.0 and whether the users would be able to control time via our animation technique. Section 4.4 describes an experiment to evaluate the performance of *TiltingMap* (TM) technique compared to traditional animation for exploring presence dynamics indicators depicted through choropleth maps. Section 4.5 describes an experiment performed with trainee users to evaluate the usability of a refined version of our prototype (i.e. *eSTIME 2.0*). Finally, Section 4.6 describes a study performed with experts to evaluate the suitability of *eSTIME 3.0*, a refined and complete version of our visualization interface, to explore daily urban mobility data through the three objects of interest.

4.2 Mutual Materials and Methods

The set of user-based evaluations performed during this thesis share the goal of assessing the usability and usefulness of our geovisualization environment throughout its several stages of development. Each experiment gathers feedback from users to improve our visual and interaction tools to achieve effectiveness, efficiency and satisfaction while supporting the querying of data to answer the domain-related questions.

Three experiments evaluate different versions of eSTIME (i.e. an improved prototype based on the outcomes and user feedback of previous experiments), while one experiment specifically evaluates the usability of the *TiltingMap* technique for time animation. Every experiment follows a similar protocol, metrics and statistical analysis plan, which allows to suggest whether our modifications were successful by comparing the same measures across experiments.

Procedure

The experiments followed a standard procedure (Figure 4.2.1) divided in six parts:

1. the *terms and conditions agreement*, which participants read and signed, authorizing us to use their anonymized data and/or images produced while undertaking the experiment only and exclusively in the context of this research. They could participate of the experiment without allowing the use of their image, in which case we would only use the data

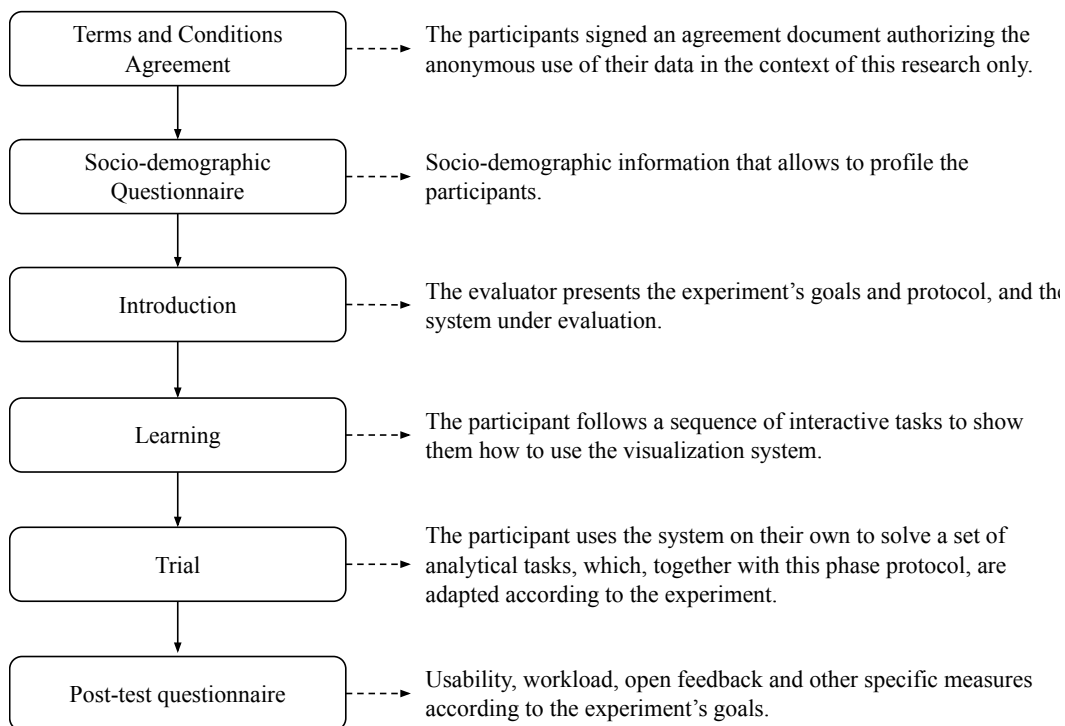


Figure 4.2.1: The general experimental protocol followed by every user-base evaluation.

generated by the participant without taking pictures of them while undertaking the experiment;

2. the *socio-demographic questionnaire*, which gathers information on participants' age, gender, occupation, education level, and personalized information regarding their experience on the subject, and using visualization systems and non-conventional interaction interfaces (e.g., tactile and tangible input). We personalized the questionnaire according to the context of each experiment;
3. the *introduction*, which comprises a presentation of the experiment goals and protocol, and a demonstration of the visual and interaction tools under evaluation. This phase takes around 10 to 15 minutes;
4. the *learning phase*, which consists of teaching the participant about how to use the visual and interaction tools. Typically, the participant follows a sequence of interactive tasks within the Control Unit interface such as opening, closing and modifying the visualizations. We personalized this phase according to temporal constraints, participants profile and experiment's goals;

5. the *trial phase*, which comprises on using the visual and interaction tools to complete a set of tasks. We adapted this phase's protocol (i.e. order of tasks, use of additional questionnaires, etc) and tasks type, complexity and amount according to the experiment design and objectives. Further, every quantitative data (i.e. completion time, response of tasks, interaction aspects) are collected during this phase; and
6. the *post-test questionnaire*, which gather participant's assessed system usability and perceived task workload (Subsection 4.2 describes the used metrics). The questionnaire also includes a field where the participant may leave their critical opinion and suggestions regarding the visualization system and/or the experiment itself.

Measures and Metrics

The usability of a system is defined as the level of suitability for the context in which it is used (Brooke, 1996). According to ISO 9241-11:2018 (2018) usability should cover the following aspects:

- *effectiveness*, which measures the extent to what users can achieve their objectives with completeness and accuracy (Forsell and Cooper, 2014);
- *efficiency*, which measures the amount of effort (time spent or cognitive load) expended in relation to the accuracy and completeness (Forsell and Cooper, 2014); and
- *satisfaction*, which refers to users' perceptions, feelings, and opinions about the product (Rubin and Chisnell, 2008).

Overall Usability To measure the overall usability of our visual and interaction tools, we used the well-known System Usability Scale (SUS) questionnaire (Brooke, 1996), which consists of a ten-item scale giving a global view of subjective assessments of usability. Each item correspond to a statement covering one aspect of system usability (e.g., need for support, training, and complexity). The method has become an industry standard (i.e. more than 1300 citations), due to being easy to administer, while providing reliable results both on large and small samples, and it is valid, i.e. it can effectively differentiate between usable and unusable systems (U.S. Dept. of Health and Human Services, 2006).

The standard version of SUS (the one we used) contains items with mixed tone – odd items have a positive tone, while even items have a negative tone. We applied the questionnaire immediately after the trial, before any debriefing or discussion to avoid bias. The respondent was asked to rate each item on a 5-points Likert scale according to their level of agreement or disagreement with it. To compute the overall SUS score, (a) each item was converted to a 0-4 scale for which higher numbers indicate a greater amount of perceived usability, (b) the converted scores were summed up, and (c) the sum was multiplied by 2.5. This process produces scores that can range from 0 to 100 (Borsci et al., 2015).

Grade	SUS score	Interpretation
A+	84.1 – 100	<i>Excellent</i> , i.e. high performance and satisfaction; no improvements are necessary
A	80.8 – 84.0	
A-	78.9 – 80.7	
B+	77.2 – 78.8	<i>Good</i> , i.e. good performance and satisfaction; minor improvements could be put in place
B	74.1 – 77.1	
B-	72.6 – 74.0	
C+	71.1 – 72.5	<i>Satisfactory</i> , i.e. average performance and satisfaction; improvements are necessary
C	65.0 – 71.0	
C-	62.7 – 64.9	
D	51.8 – 62.6	<i>Below average</i> , i.e. inadequate performance and satisfaction; major improvements are necessary; borderline re-design
F	0 – 51.7	<i>Inadequate</i> , i.e. one cannot achieve performance neither satisfaction using the system; the design must be retaught

Table 4.2.1: The Curved Grading Scale (CGS) proposed by Sauro and Lewis (2016) for assigning grades to usability as a function of SUS scores.

In the experiments with a temporal constraint, we assessed usability via the UMUX-Lite questionnaire (see Appendix D), which corresponds to a reduced alternative to the SUS questionnaire that uses the two positive items of another reduced alternative, the Usability Metric for User Experience (UMUX). To compute the overall UMUX-Lite score, (a) we subtract 1 from each 5-point item, (b) add them together, and (c) multiply by 100/12. Then, we apply a regression equation proposed by Lewis et al. (2013) to bring the UMUX-Lite score into correspondence with the SUS score.

We interpreted the usability scores based on the Curved Grading Scale (CGS) proposed by [Sauro and Lewis \(2016\)](#) to assign grades as a function ranging from F (absolutely unsatisfactory) to A+ (absolutely satisfactory) (Table 4.2.1). The authors analyzed data from 446 studies and more than 5,000 individual SUS responses, from which the overall mean score of SUS was found to be 68 ($SD = 12.5$) – the center of the range for a grade C.

Response Accuracy In each experiment, we asked participants to complete a set of domain-related tasks based on the system of tasks proposed in section 3.4, which would overall require them to discover or describe mobility patterns of a particular population over space, time and thematic dimensions. Therefore, we use the response accuracy (i.e. the exactitude of the mobility pattern description according to the tools they dispose) to measure the effectiveness of our visual and interaction tools. The responses were subjectively scored on a 10-points scale ranging from 0 (totally inaccurate) to 1 (totally accurate) (i.e. 0, 0.1, 0.2, ..., 1), according to the responses formulated by the expert who designed the tasks while using the same visual and interaction tools used by the participants. The scores are multiplied by 100 to describe accuracy as the percentage of correct answers.

Completion Time We measured the amount of effort required to achieve accuracy through the completion time (total and per task), amount of interactions, and perceived task workload. The completion time and amount of each interaction type were automatically collected via a questionnaire interface embedded in the Control Unit that mainly presents tasks and, eventually, collect responses. The participant was asked to read the task on this interface, and tap on a starting button that recorded the timestamp that marked the beginning of the task. After completing each task, they would return to the questionnaire interface and proceed to the next task, which action recorded the timestamp that marked the end of the task. During the whole process of completion the task, their interactions with visualizations (e.g., zooming in/out, time units selection, opening/closing) were recorded.

Workload We gathered users self-reported workload through the NASA Task Load Index (TLX) ([Hart and Staveland, 1988](#)), which is a multi-dimensional rating procedure that provides an overall workload score based on a weighted average of ratings of six workload-related factors (sub-scales):

- *Mental Demand (MD)*, which refers to the amount of mental activity that was required (e.g., thinking, deciding, calculating, remembering, looking, searching);
- *Physical Demand (PD)*, which refers to the amount of physical activity that was required (e.g., pushing, pulling, turning, controlling, activating);
- *Temporal Demand (TD)*, which refers to the amount of pressure felt due to the rate at which the task elements occurred, i.e. was the task slow and leisurely or fast and frantic?
- *Own Performance (OP)*, which refers to how successful one think they were in doing what they were asked to do and how satisfied they were with what they accomplished.
- *Effort (EF)*, which refers to how work one had to work (i.e. mentally and physically) to accomplish their level of performance; and
- *Frustration (FR)*, which refers to how insecure, discouraged, irritated, and annoyed versus secure, gratified, content and complacent one felt.

The evaluation procedure consists of two parts: a pairwise comparison of factors, where the respondent should choose the member of each pair that provided the most significant source of workload variation in the task, and rating scales, where the respondent should rate in a 100-points scale the magnitude of each factor in the task they just performed. In order to reduce complexity when rating each factor, we use a 10-points scale and multiply the rating of each statement by 10.

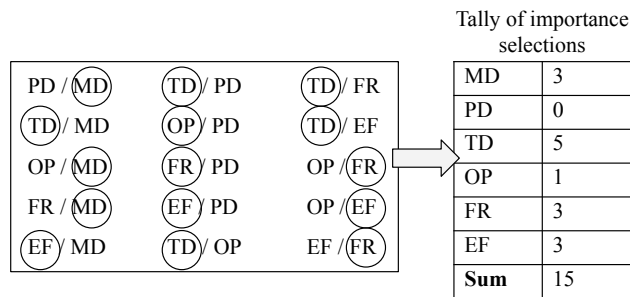
To compute the workload score of each sub-scale, (a) we tallied the factors selection in the pairwise comparison, and (b) multiplied the result by related statement's rating (Figure 4.2.2). This process produces scores that can range from 0 to 500 for determining the importance of each workload-related factor. To compute the overall workload score, we sum the scores of sub-scales and divided it by 15, which is the number of pair-wise comparisons. This process gives scores that can range from 0 to 100.

In the experiments with a temporal constraint (i.e. maximum time participants could grant to the experiment), we applied a modified version of the NASA TLX questionnaire that consists on eliminating the weighting process all together. This version is referred to as Raw TLX (RTLX), and it has

been shown to be as sensitive as the original version (Hart, 2006). The scores per factor correspond to the rating value on each statement. To compute the overall workload score, we average the scores of each factor. Analogous to the original version, we use a 10-points scale for the ratings, which result is multiplied by 10 to produce scores that can range from 0 to 100.

a) Pairwise comparison of factors

Instructions: select the value of each pair that provided the most significant source of workload variation in the task



b) Rating scale

Instructions: select the value on each scale that represents the magnitude of each factor in the task you just performed

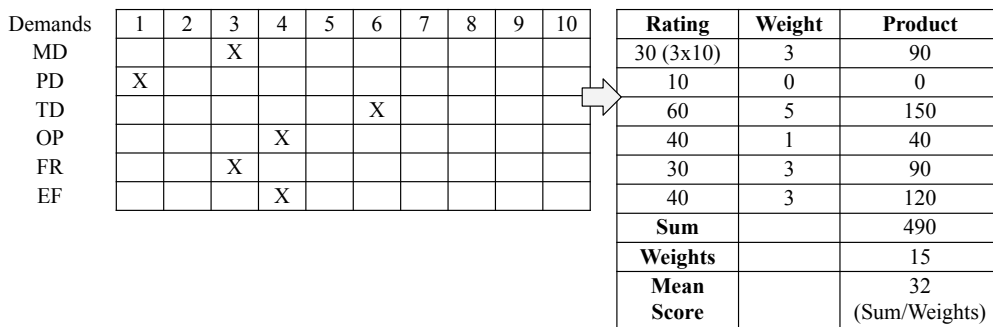


Figure 4.2.2: The process of computing the mean workload score from the NASA-TLX questionnaire. Adapted from: Hart and Staveland (1988).

The questionnaires were applied either at the post-test phase of each experiment or right after each experimental condition, when a formal experiment were in place. Exceptionally, we have not measured self-reported workload during the evaluation of the *TiltingMap* technique due to temporal constraints, i.e. we tested many experimental conditions during a one hour maximum interval.

Statistical analysis of empirical data

The outcome of user experiments are qualitative and quantitative data collected through the aforementioned metrics. This information can help us to

accept or refuse the hypotheses that drove each experiment. Therefore, we subjected the data to a statistical analysis process to compare the results between groups, when possible. We set a 95% confidence level to determine whether the difference of means between groups is statistical significant. However, since our experiments involve human beings and the data is mostly subjective, we sometimes accept a 90% confidence level in the difference of means in order to produce hypotheses that could explain the results.

We subjected the variables to a decision diagram to decide which statistical test was appropriate to compare two or more variables (Figure 4.2.3). Firstly, we performed a Shapiro-Wilk Normality test (Ghasemi and Zahediasl, 2012) of the null hypothesis that verifies whether the data come from a normal distribution, and a Fligner-Killeen test (Conover et al., 1981) of the null hypothesis that verifies whether the variances of each group are the same. In case the data pass both tests (i.e. $p < .05$) we performed a parametric test through a One-Way ANOVA (Quirk, 2016) test for comparing more than two groups, or a paired/unpaired (depending on whether the data come from the same individuals or not) Two-Samples t Test (Student, 1908) for a comparison between exactly two groups.

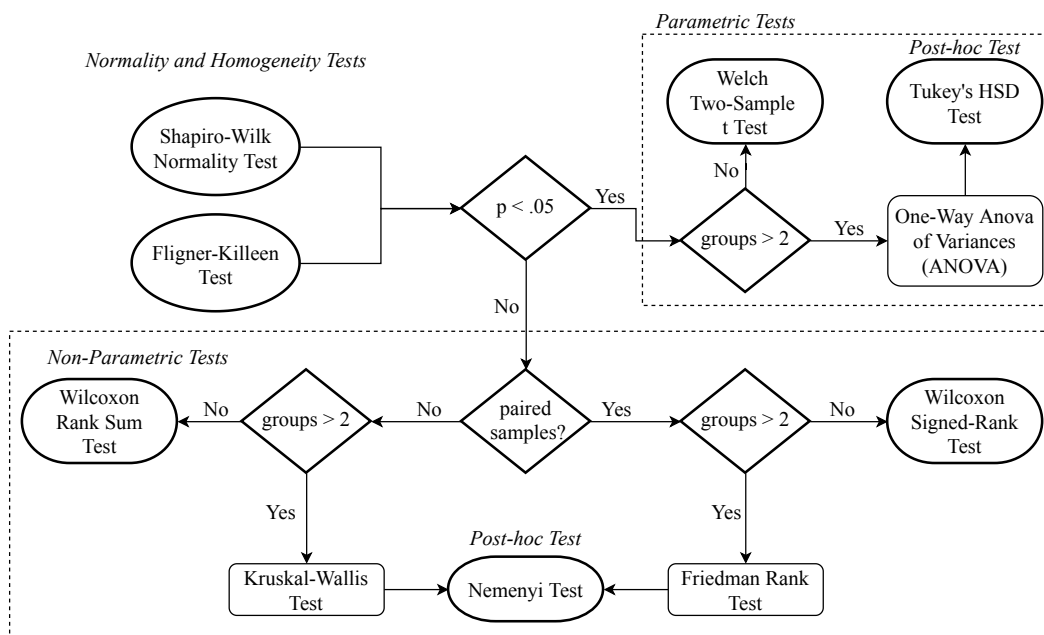


Figure 4.2.3: The workflow for performing the statistical analysis of the output data of the user studies.

Otherwise, when the data do not present a normal distribution nor equal variances, we performed a non-parametric test. In case the comparison involve

more than two groups we performed a Friedman Rank test (Friedman, 1937) for paired or a Kruskal-Wallis test (Kruskal and Wallis, 1952) for unpaired groups. To compare the difference of means between exactly two variables we performed a Wilcoxon (Wilcoxon, 1945) signed-rank test for paired, or a rank sum test for unpaired groups. Further, we ran post-hoc tests in case we find statistical significance when testing three or more groups: Tukey’s range test after One-Way ANOVA, and Nemenyi test after Friedman and Kruskal-Wallis tests.

For the sake of reproducibility, the output data of the user studies and the scripts used to analyze it, including an automated version of our decision diagram are available at <https://gitlab.com/amenin/estime---user-studies>. The whole data was processed and analyzed using the R statistical and graphical environment (R Development Core Team et al., 2011). Particularly we used *tidyverse* (Wickham, 2017) and *plyr* (Wickham, 2011) packages for structuring the data, and *ggplot2* (Wickham, 2016) package for generating graphical charts. The *stats* package, which is part of R, provide the majority of statistical methods mentioned above. Further, we use the post-hoc Nemenyi test functions provided by the PMCMRplus (Pohlert, 2020) package, and the *glht* function provided by the *multcomp* (Hothorn et al., 2008) package for running the Tukey’s range test.

4.3 Experiment I: eSTIME v1.0

In this experiment, we assessed whether our first prototype, eSTIME v.1.0, was capable to assist users on solving analytical tasks regarding the discovery/identification of daily urban mobility patterns. The visualization and interaction tools available enabled an analysis at the population level through indicators that describe the territory, travel flows and trips. However, the thematic dimension of data was not yet fully integrated, supporting only the exploration of *attribute share* indicator per transportation modes. We also investigated how users employ the *TiltingMap (TM)* technique to explore the variation of indicators (i.e. derived from the presence matrix) over time, and which interaction style they prefer (i.e. circular or linear tilting movement).

4.3.1 Visual and Interaction Tools

Regarding the visualization components, eSTIME v1.0 contains a first design of the *flows diagram*, the *mobility wheel*, and the *map view*. As an attempt to reduce bias during the experiment, we identified the locations through numerical codes (i.e. defined in the survey), instead of their names. At this stage, we visualized flows through a basic chord diagram design (Figure 4.3.1a), which arcs represent color-coded spatial locations. The ribbons' thickness encodes flow magnitude, and color indicates the flow origin. For instance, Figure 4.3.1a (right) highlights the outgoing and incoming flows of location 2, where the navy blue ribbon connecting locations 1 and 2 indicates an incoming flow from location 1, while the green ribbon (same color as location 2) represents an outgoing flow from 2 to 7 (i.e. incoming flow of location 7).

The mobility wheel consists of a two-part chart (Figure 4.3.1b). The first component is the wheel itself, which outermost ring encodes mobility rate via color intensity and the innermost ring depicts the transportation modes share per time unit. The set of bar charts displayed side-by-side next to the wheel allow one to zoom into the transportation modes distribution, and to compare them across six time units (Figure 4.3.1b – right). These charts are progressively displayed/removed as the user finds it necessary by directly selecting time units on the time picker. A list of valid charts (i.e. the spatial locations for which they are built) is available close to the time picker, so the user can choose on which mobility wheel to display the bar chart. Upon a bar chart removal, the remaining plots are re-arranged to fill the leftmost empty tiles.

The Control Unit contains a map view, where indicators of attractiveness, presence density and fluctuation can be visualized through a choropleth map (Figure 4.3.2e). We used a side navigation menu (Figure 4.3.2a) to manage the visualizations on each display (i.e. control unit and dashboards). This menu has three hierarchical sub-menus: territorial partition, indicator, and visualization spaces (i.e. analytical dashboards), and two buttons: memory and submit. We allowed the user to save the visualization at its current state (i.e. regarding territorial partition, spatial location, time unit) by using the *save* icon under each indicator. A list of these recordings was available by clicking on the *memory* button. Further, the *information* icon provided a detailed description of the corresponding indicator. To display/remove an indicator from the control unit or an analytical dashboard, the user must follow a four-step process:

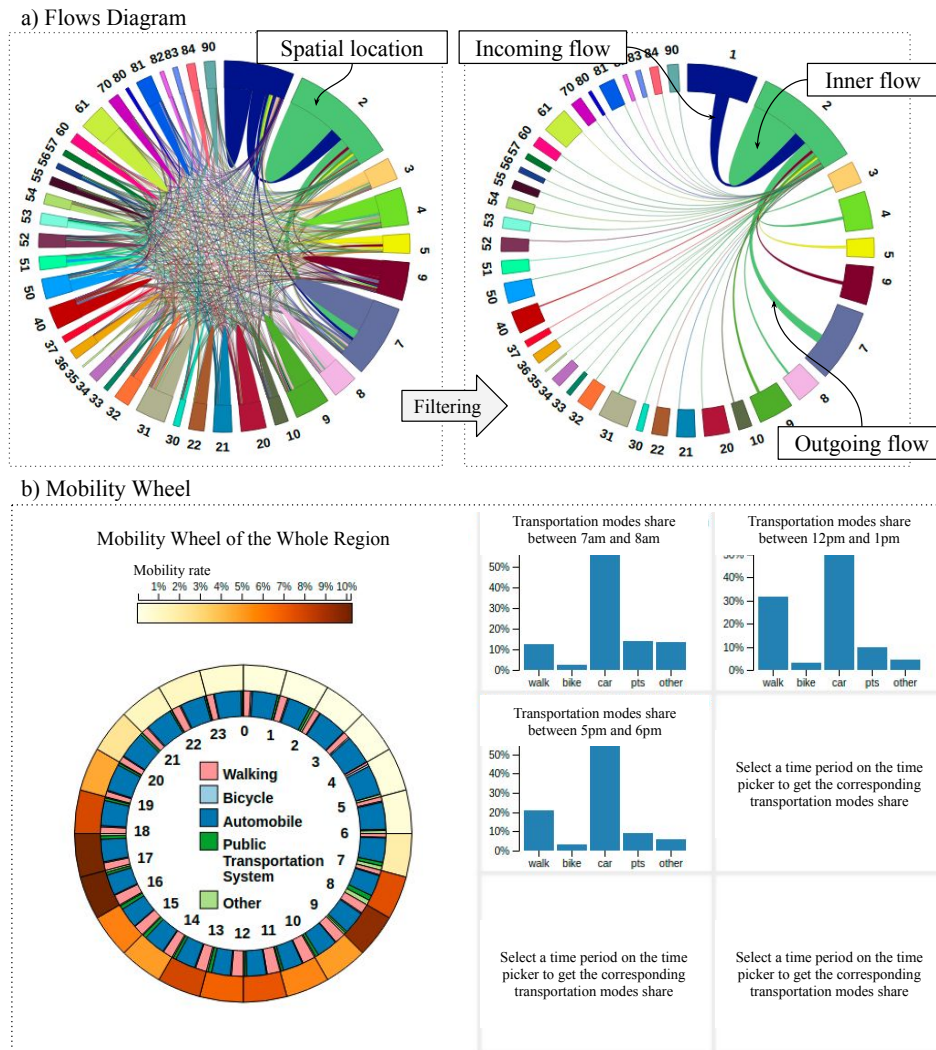


Figure 4.3.1: eSTIME v1.0: (a) flows diagram and (b) mobility wheel.

1. Choose the territorial partition: 12 sectors (large areas), 39 sectors (intermediate areas), 97 sectors (polling districts);
2. Define the indicator(s), action and display: under the chosen indicator, click on the tablet (1st) or desktop (2nd) icon, which automatically selects the indicator and display where to visualize/remove it from: the control unit or an analytical dashboard, respectively. The icon becomes green when the indicator was successfully visualized on a display. This process can be applied to several indicators at once;
3. Choose the analytical dashboard: in case the desktop icon is enabled for any indicator selected in the previous step, select the proper display

to apply the changes (enumerated according to the connection order) under the *visualization spaces* section;

4. Apply the changes: click on the submit button at the bottom, which firstly applies the removal actions, shifting the remaining visualizations to fill the leftmost empty windows, then it displays the corresponding visualization of each indicator on the leftmost available window in the dashboard.

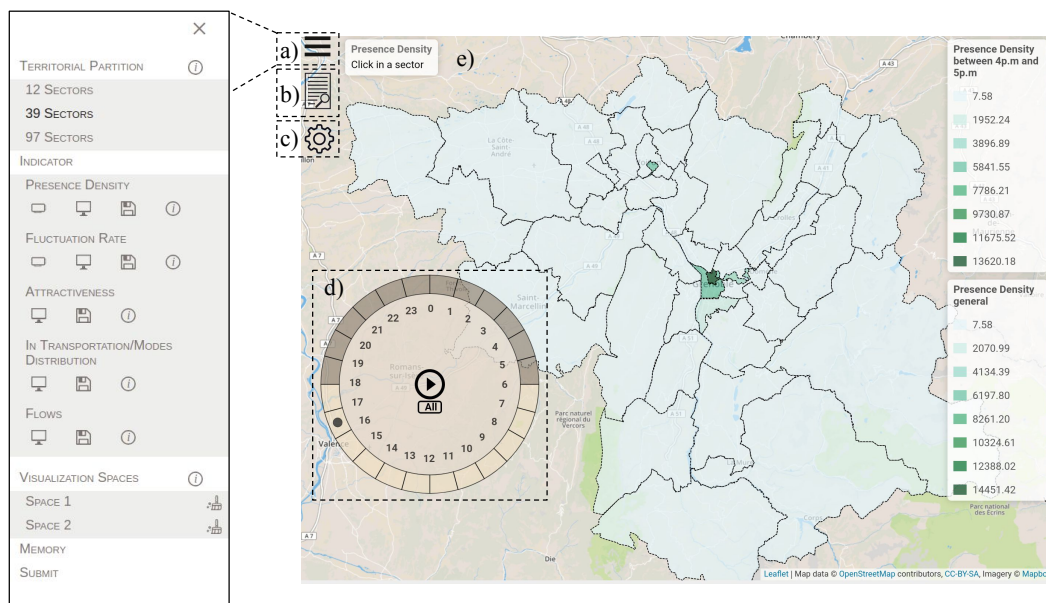


Figure 4.3.2: eSTIME v1.0: Control Unit interface. (a) A side navigation menu allows the opening/closing of indicators on the dashboards. (b) An automatic questionnaire guide the analytical tasks during the Trial phase and records the tasks' completion time. (c) The settings serve to change the time picker format: circular or linear (d), and to manage the questionnaire. The map (e) enables spatial filtering and the visualization of presence-related indicators.

The above process displayed the indicator(s) for the whole region. In order to explore the indicator for a particular spatial location, the user must open a context menu embedded in that location on the map, which will present them with the possible indicators and analytical dashboards where to display it.

The interface contained yet a *form* icon, which opens an automatic questionnaire used during the experiment to present the tasks to the users and record the tasks' completion time. The TM technique was implemented via a

circular time picker as the default, and could be changed to a linear one via the *settings* icon (Figure 4.3.3), which action was restricted to the experimenter during the evaluation.

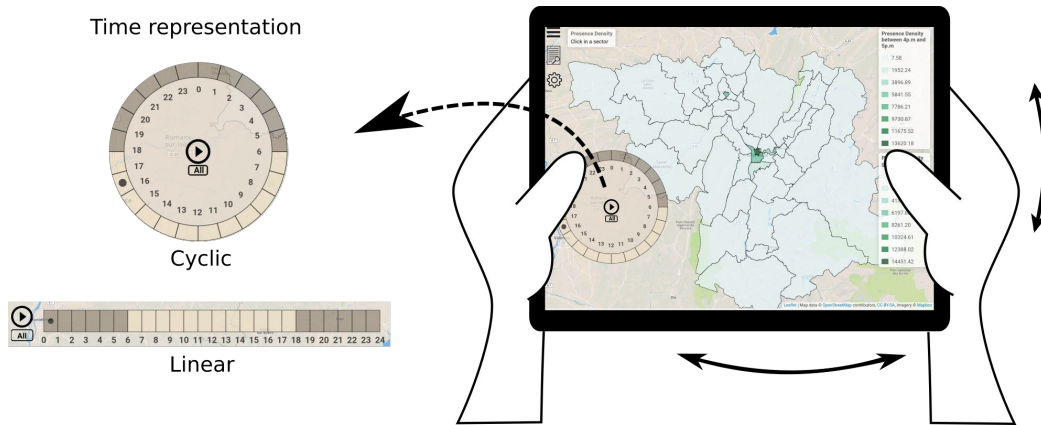


Figure 4.3.3: The *TiltingMap* technique can be used through a circular or a linear time picker, which affects the tilting movement (rotational and left to right, respectively). The time representation can be changed at any time.

4.3.2 Hypotheses

In this experiment, the overarching hypothesis is that *eSTIME v1.0* can enable the understanding of the urban structure and the usage of different spatial locations through the visual exploration of indicators describing travel flows and presence dynamics (over time) of people throughout the territory. On a more particular level, we investigated the following hypotheses:

H1: *Users will effectively and efficiently complete analytic tasks regarding urban mobility phenomenon described by travel flows, trips, population and territory dynamics.*

The indicators represented in this version of our visualization interface allow to explore the spatio-temporal variation (and thematic at a certain degree) of indicators describing two objects of interest within urban mobility data. Furthermore, the customizable aspect of the interface enables one to display and remove views according to the ongoing analysis, and to explore the variation of indicators by juxtaposing views or using animation, which allows the user to choose the most appropriate method

according to their needs. Thus, we believe this flexibility will help them to quickly retrieve these urban mobility patterns enabling an effective and efficient completion of the analytical tasks.

H2: *The circular time picker will positively affect response accuracy.*

The circular design of the time picker is based on the metaphor that daily mobility patterns repeat themselves each 24 hours. Thus, we believe that the circular movement will help users to identify recurrent patterns, since they do not need to shift the time selector back to the first time unit in order to restart the daily pattern, but instead they follow a continuous animation.

H3: *Participants will prefer to use the linear time picker over the circular one.*

Using the circular movement requires a rotational movement (3 degrees of freedom – 3DoF, i.e. pitch, yaw, and roll) to track whether the tablet was tilted left or right, up or down, or a combination of both, while the linear movement only requires 1DoF (i.e. yaw) for tracking whether the tablet was tilted left or right. Therefore, since the rotational movement may hinder the control of the circular time picker and the users are quite accustomed with timelines, they might prefer the later, reducing cognitive load.

4.3.3 Materials and Methods

Participants

Thirteen (13) unpaid persons (5 female), aged from 26 to 57 years old ($M = 36$, $SD = 10.01$), took part in this experiment. The majority of participants were French native speakers with good understanding of English (self-reported), which information helps to avoid bias, since tasks and the visualization interface were provided in English. Nevertheless, the experimenter would administer the experiment in French to prevent misunderstandings.

Although our volunteers lived in the studied area during a time span from less than 2 months up to 57 years ($M = 21$, $SD = 19.33$), we did not observe any correlation between this factor and their accuracy on completing the analytic tasks. Similarly, their prior knowledge regarding the human mobility patterns within the studied area and their experience on Geographical Infor-

mation Systems (GIS) ($M = 2.76$ and $M = 3.53$ in a 5-point Likert scale, respectively) did not show any influence on the results.

Experimental Conditions and Tasks

The experiment followed a completely randomized design to explore the aforementioned assumptions, which experimental conditions correspond to the tilting movement necessary to control time animation:

- a) the **circular**, which represents time as 24 rectangles (i.e. one per time unit) placed over a circular axis and requires the use of 3DoF to perform a rotational movement in a clock- and counterclockwise direction producing tilting angles that are mapped into time units; and
- b) the **linear**, which represents time as 24 rectangles placed over a linear axis and requires the use of 1DoF to perform a movement from left to right and contrariwise producing tilting angles that are mapped into time units.

Following a within-subjects design, we assigned each participant to both treatment groups, and asked them to complete two different sets of tasks. Each set contains six tasks prepared by a researcher specialized on human mobility. The overall complexity (i.e. the amount of variables and therefore views necessary to solve the task) is equivalent in both sets. Nonetheless, this complexity increases from one task to another within each set. The tasks can be elementary or synoptic regarding the spatial and temporal dimensions of indicators.

Table 4.3.1 presents the types and description of both sets. The types of tasks were defined accordingly to our system of tasks (see Section 3.4), for querying indicators over space and time (attributes and objects were not considered at this stage). The studied territory was the urban area of Grenoble, which elementary spatial components were a single location $s \in S$, and the synoptic components were sets of locations S . The region was considered an elementary spatial component formed by all locations taken together as a whole. The elementary temporal components were time units (i.e. one-hour intervals) $t \in T$, and the synoptic components were sets of time units T . Analogously to the spatial dimension, the aggregation of all time units form

a singular 24-hour interval, which was considered as an elementary temporal component. In this experiment, the elementary tasks in respect to the temporal dimension targeted three particular time units: morning (between 7am and 8am), noon (from 12pm to 1pm), and evening (from 6pm to 7pm).

ID	Set 1	Set 2
1	$s \rightarrow t \rightarrow M$: Give the presence density of location 5 during the morning period.	$s \rightarrow t \rightarrow M$: Give the fluctuation rate of location 6 during the morning period.
2	$s \rightarrow T \rightarrow M$: Give the mobility rate for the whole region during the morning and evening periods.	$t \rightarrow S \rightarrow M$: List the five most attractive locations in descending order of attractiveness.
3	$s \rightarrow T \rightarrow M$: Give the transportation modes share for the whole region during the morning, noon and evening periods.	$S \rightarrow t \rightarrow M$: Identify the time period when the two most attractive locations have the highest mobility rate.
4	$S \rightarrow t \rightarrow M$: Identify where the majors incoming travel flows to the three most attractive locations over 24 hours come from.	$S \rightarrow t \rightarrow M$: Identify where the major outgoing travel flows from the two less attractive locations over 24 hours are going to.
5	$S \rightarrow T \rightarrow M$: Classify locations 1, 6, 61 and 51 according to the transportation modes share during the morning, noon and evening periods.	$S \rightarrow T \rightarrow M$: Identify the two locations with the higher overall mobility rate among locations 2, 6, 61, and 51.
6	$T \rightarrow S \rightarrow M$: For each time period (i.e. morning, noon, evening), choose a location that presents a positive fluctuation rate.	$T \rightarrow S \rightarrow M$: For each time period (i.e. morning, noon, evening), choose a location that presents a negative fluctuation rate.
	$S \rightarrow T \rightarrow M$: Then, for each chosen location, give the transportation modes share during the morning, noon, and evening periods.	$S \rightarrow T \rightarrow M$: Then, for each chosen location, give the transportation modes share during the morning, noon, and evening periods.

Table 4.3.1: The sets of analytic tasks applied during the Experiment I.

Procedure

The volunteers were directly contacted by e-mail. We asked them to digitally sign the Term and Conditions agreement (see Appendix D.2) in case of accepting to participate of the experiment, and to answer the socio-demographic questionnaire (see Appendix D.3). An experimenter guided each individual session, which duration varied from one hour and 15 minutes to two hours and a half. The average duration of each experimental condition was 26 minutes. The session starts with a presentation about the thematic objectives of eSTIME and the experiment's goals, and a short demonstration of the visual and interactive tools usage. Afterwards, during the learning phase, the participant was given a moderate time to freely explore the visual and interactive tools (from 10 to 15 minutes).

The trial phase was divided into two parts, one per experimental condition. We counterbalanced the order of conditions and sets of tasks to ensure that the order does not affect the results of the experiment (see Table 4.3.2). Participants could ask for clarifications about the visual and interaction tools and/or the tasks themselves during the whole experiment time. The Control Unit interface embedded a slide-like presentation of tasks, displaying the tasks description one-by-one together with a step-by-step procedure to open and explore the visualizations necessary to complete the tasks (see Appendix D.1 for a complete description of tasks). This interface would also record the completion time of each task upon the user's confirmation that they finished it. Although time was measured, the participants were not given any temporal restrictions for completing the different phases of the experiment.

ID	Part 1	Part 2
1	linear + Set 1	circular + Set 2
2	linear + Set 2	circular + Set 1
3	circular + Set 1	linear + Set 2
4	circular + Set 2	linear + Set 1

Table 4.3.2: Combinations of experimental conditions and sets of tasks used in both parts of the Trial phase of Experiment I.

After each experimental condition, participants were asked to report their perceived workload by answering the NASA TLX questionnaire. Finally, in the post-test phase, we applied the SUS and preference questionnaires, and

asked users for their opinion about the visual and interaction tools, and the experiment itself.

Apparatus

Figure 4.3.4 presents the environment setting used in this experiment. The analytical dashboard was displayed on a 24-inch LED monitor, with a 1920x1200 pixels resolution at 60 Hz and an aspect ratio of 16:10. The Control Unit interface run on a 9.7-inch Samsung Galaxy Tab S3, with a 2048x1536 pixels resolution and an aspect ratio of 4:3. An extra laptop, which characteristics are negligible, served as support for users entering the answers of the analytic tasks and questionnaires (pre- and post-test).



Figure 4.3.4: Environment setting of Experiment I. The tablet served as the Control Unit, the desktop monitor held the analytical dashboard, and the laptop served as support for typing the tasks' answers in a digital form.

4.3.4 Results

Completion Time and Accuracy

Overall, we did not observe statistical significance between the experimental conditions regarding neither the response time nor accuracy. Participants took in average 26 minutes to answer each set of questions and they provided around 86.25% of correct answers under both experimental condition. As expected, the completion time increases according to the complexity of tasks Figure 4.3.5(left) regardless the experimental condition.

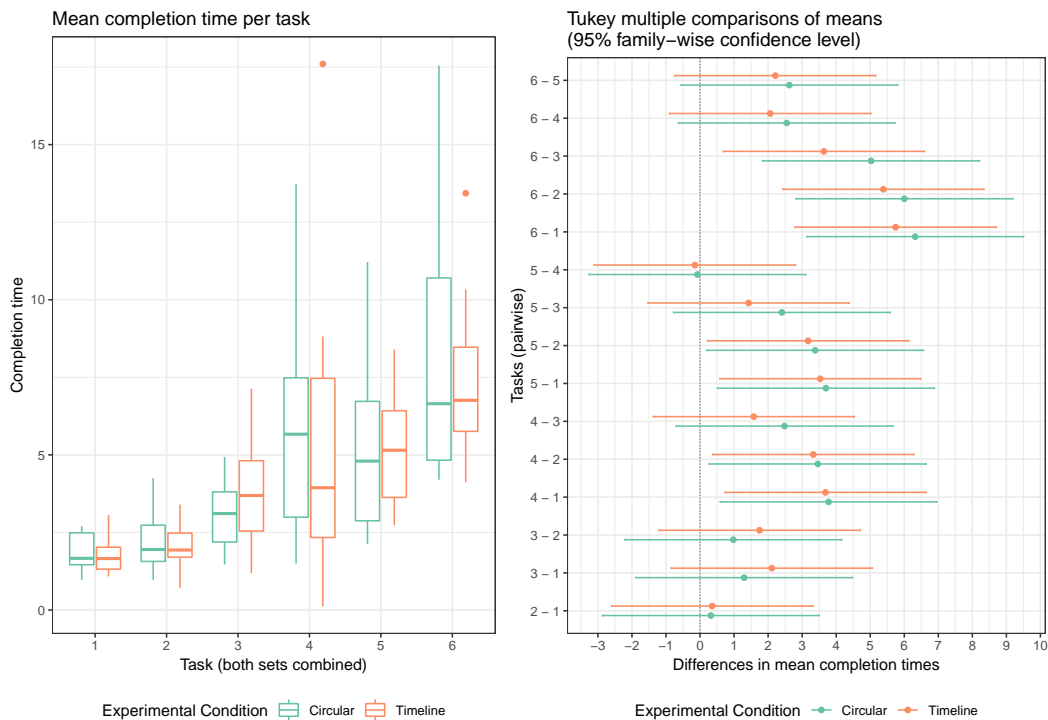


Figure 4.3.5: Comparison of mean completion times per task (both sets combined) across experimental conditions.

The graph of intervals (Figure 4.3.5 – right) presents a pairwise comparison of completion means between tasks, which we interpret as follows: if an interval contains zero, we cannot conclude a difference between the two means; if the interval does not contain zero, then a difference between the two means is supported. From the analysis of intervals, we observed that the difference of completion times was statistical significant between the two first tasks and the three last ones. The 3rd task is somehow neutral regarding the completion

time, which difference was only statistical significant with regard to the 6th task, a composite and complex task regarding both thematic input and the necessary amount of charts for interpretation.

We observed a 56% correlation between the completion time and accuracy in the circular experimental condition ($p = .058$), which suggests that users who took longer to answer the questions also gave more accurate answers. We also observed that the older the participants, the longer they took to complete the tasks using the linear interaction style, which variables are 72% correlated ($p < .01$). However, when using the circular time representation, completion time was about the same regardless of participants' age.

Workload

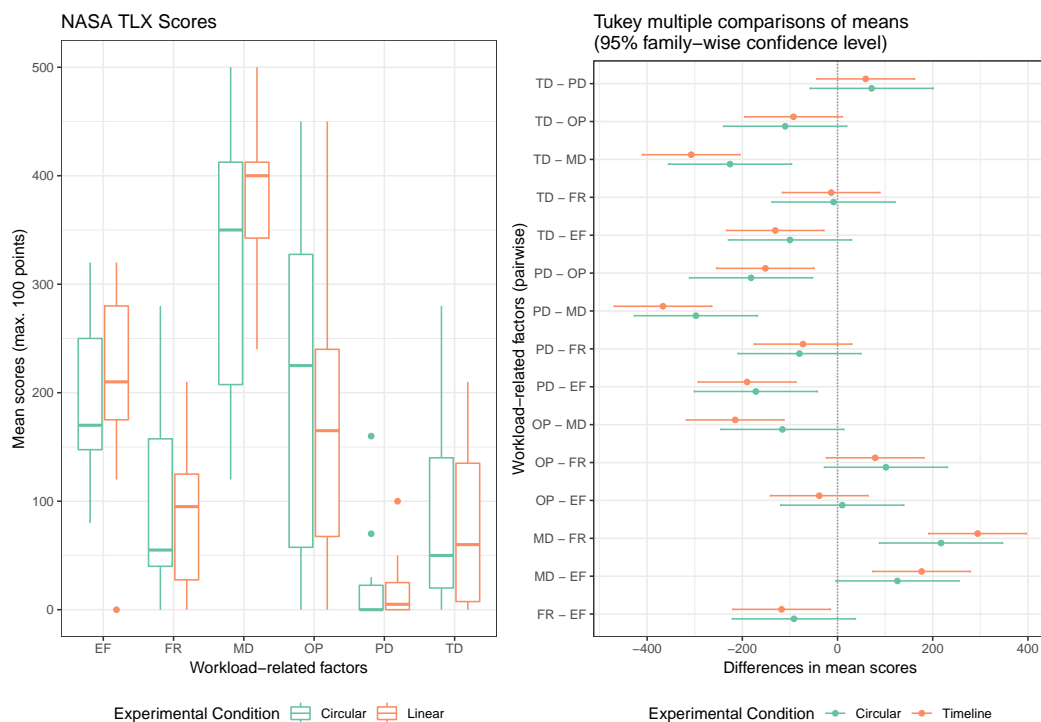


Figure 4.3.6: Comparison of mean scores of NASA TLX workload-related factors across experimental conditions.

The overall mean score of NASA TLX questionnaire was similar in both experimental conditions ($M = 63.7$, $SD = 9.83$ for circular, and $M = 63.6$, $SD = 6.20$ for linear). Although the mean scores per workload-related factor

were similar between the conditions (Figure 4.3.6 – left), we did observe statistical significance within each experimental condition while comparing factors in a pairwise fashion (Figure 4.3.6 – right).

Overall, regardless the experimental condition, the mental demand (MD) appears to be the main source of workload, while the physical demand (PD) did not significantly affected overall workload. Particularly, in the linear condition, we found statistical significance in the difference of mean scores of MD and every other factor indicating it was the most important source of workload. However, in the circular condition, although the mean scores of MD were higher than the remaining factors, only the difference with PD, temporal demand (TD) and frustration (FR) ($p < .001$) was statistical significant. PD was also significantly lower than effort (EF) and subjective own performance (OP) ($p < .001$) in both conditions. Moreover, in the linear experimental condition, the difference between EF and FR scores was statistically significant, suggesting that users found it to be less frustrating than effortful ($p < .001$), which effort is likely related to the high scores of mental demand.

We found correlations within certain workload-related factors and between workload scales and response accuracy, completion time and users' age (see Table 4.3.3). In both experimental conditions, a negative correlation suggests that when MD is perceived as an important source of workload, users tend to perceive little PD. In the linear experimental condition, the most users perceived PD as an important source of workload, the lower was the response accuracy. Under both conditions, the scores of OP appears to reduce as MD and FR increase, which indicates that users seem to believe they failed the task when it was high mentally demanding or frustrating. Nevertheless, no correlation was found within MD, FR and response accuracy.

Variables	Circular Movement		Linear Movement	
	R	p	R	p
MD & PD	-0.59	0.032	-0.6	0.029
PD & Response Accuracy	No correlation		0.69	0.016
OP & MD	-0.83	< 0.001	-0.51	0.078
OP & FR	-0.51	0.091	-0.61	0.037
MD & Age	0.52	0.084	0.6	0.038
FR & Completion Time	No correlation		-0.4	< 0.001

Table 4.3.3: Summary of correlations found within workload-related factors and/or other variables.

Regarding the users profile, older people seem to perceive the task more mentally demanding than younger ones. We have found a 52% correlation between these variables in the circular experimental condition ($p = .084$) and a 60% correlation in the linear condition ($p = .038$). We found a negative 40% correlation ($p < .001$) between completion time and FR, which suggests that higher completion times reduces frustration. We believe that higher exposition times to the visualization interface helped users to get accustomed with it, mastering the visual and interaction tools, consequently reducing their frustration feelings.

Usability and Preference

The mean score of the SUS questionnaire was of 58.3 ($SD = 16.5$) from a maximum score of 100 points. This correspond to a grade D (see Table 4.2.1), which is considered below average, requiring major improvements for allowing the user to achieve performance and satisfaction while using the system.

We measured preference by asking users to rate the following statement: “I prefer interacting with the timeline rather than with the cyclic time representation” in a 5-points Likert scale. Overall, users agreed with it, indicating their preference for linear over circular tilting movement ($M = 3.53$, $SD = 1.19$). Participants justified this choice through arguments such as “the linear representation is more practical than the circular one”, “the lower degrees-of-freedom ease the manipulation”, “we are more used to this kind of representation”, and “the circular format made it difficult to place the marker on a particular time period”. Paradoxically, the participants who did not agree with this statement, argued that “the circular representation was easier to manipulate” and that “the linear one required more extreme tilting”.

Although the participants could see the potential of eSTIME, we found plenty of room for improvement. Some participants found that the tasks were difficult because of their background, since they were not experts in the field of human mobility. They reported having trouble interpreting the flows diagram and they would have liked to interact with the visualizations displayed on the dashboard, along with a details-on-demand feature to improve the interpretation of data in each chart. Recurrent comments were made regarding the time dedicated for learning how to use the interface, which they would have liked to be longer so they could have mastered the visual and interaction tools.

4.3.5 Synthesis

Hypotheses Assessment

H1: *Users will effectively and efficiently complete analytic tasks regarding urban mobility phenomenon described by travel flows, trips, population and territory dynamics.*

The participants were able to complete every task with a high accuracy, that is they provided more than 80% of correct answers. This positive result was acquired despite the unsatisfactory usability and workload scores, and the troubles understanding some of the visualizations. However, improvements are necessary to increase usability, since this satisfactory response accuracy was positively correlated to completion time, which should be shorter for implementing the system on experts' work environment. Therefore we **refuse** this hypothesis, since effectiveness was achieved at the expense of efficiency and satisfaction.

H2: *The circular time picker will positively affect response accuracy.*

We did not observe any statistical significance supporting this hypothesis. The response accuracy did not present any observable differences between the experimental conditions. Hence, due to lack of evidences we cannot accept neither refuse this hypothesis.

H3: *Participants will prefer to use the linear time picker over the circular one.*

Our participants preferred to use the linear representation of time over the circular one, which arguments included the lower degrees-of-freedom needed to tilt the device. Therefore, we can **accept** this hypothesis.

Overall, the opinion of participants suggest that our approach was interesting and has potential to answer our research questions. However, the assessed usability of this version of eSTIME is unsatisfactory, and participants reported a high overall workload with mental demand being considered the main source of workload. These results indicate that major improvements are necessary to make our visual and interaction tools user-friendly, while allowing the users to achieve performance and satisfaction.

The only source of information about how to read and interpret the visual representations was the experimenter, who explained the indicators and visualizations during the learning phase. Therefore, users reported that the

absence of a tutorial and accurate legends hindered the process of interpreting the visualizations, specially regarding the flow diagram, which they were unfamiliar with. The absence of a feature that provides details-on-demand hindered the completion of elementary tasks, since they require users to extract a precise information from the chart (i.e. presence density, mobility rate), which accuracy was impossible to accomplish only via the interpretation of colors.

Our interaction mechanism between the tablet and the analytical dashboards should be re-taught. The four-step process required on the main menu and the existence of one sub-menu per spatial location for opening/closing visualizations turned out to be confusing and hard to remember. Regarding the sub-menu on each spatial location, one participant said that “it would be more intuitive to select the indicator and then the location for which to display it”, not the other way around. We should also include more perceptual cues, such as to highlight the spatial location on the map upon its selection for filtering flows in the flow diagram.

The lack of experience on the domain of human mobility was pointed several times as a difficulty for completing the tasks, which could explain the high scores for mental demand and effort, and the negative correlation between how they evaluate the quality of their performance and their perceived mental demand and frustration.

We could gather feedback regarding the TM technique such as how pausing/resuming the animation hindered time units selection, since the user would slightly move the tablet while performing the action. The physical demand for animating time via the TM technique appears to be low regardless the movement style, which is a positive result since we would like the users to leverage the movement and position of their arms and wrists, without having to switch their attention from the visualization. Nevertheless, further studies are necessary to evaluate the added value of TM for exploring the variation of data over time.

The outcomes of this experiment allowed us to improve our prototype according to the feedback of participants and our own observations during the trials. Two new user experiments were then conducted to evaluate the improved prototype. The first experiment compares the performance of the TM technique with traditional animation regarding user perception and map reading (Section 4.4). The second experiment evaluates the re-designed prototype, i.e. eSTIME v2.0 (Section 4.5).

4.4 Experiment II: TiltingMap

The previous experiment revealed some of users preferences, criticisms and suggestions regarding the *TiltingMap* (TM) technique. However, the chosen experiment protocol could not reveal the actual added value of our movement-based interaction technique. Therefore, we designed this experiment to explore the TM technique's effects on the effectiveness of animated map reading. We compared the TM technique using both tilting movement styles (circular and linear), and the traditional animation, which interaction is provided through the conventional mouse and direct touch. Since our Control Unit runs on a tablet, we included the touch interaction to verify whether using direct touches would affect the performance of traditional animation.

4.4.1 Hypotheses

In this experiment, the overarching hypothesis is that using the proprioceptive sense (i.e. the sense of self-movement and body position) triggered by the movement of hands and wrists for tilting the device will improve map reading compared to traditional animation, since the user could use the position and orientation of their hands and wrists as reference recall to the visualized information. On a more particular level, we investigated the following hypotheses:

H1: *User performance will be similar whether interacting with traditional animation via mouse clicks or direct touch.*

Despite the fact that we are very used to interact with virtual information via the traditional mouse and keyboard devices, we use our fingers to interact with objects in real life. This naturalness in the way we interact in the physical world has made the introduction of smartphones into our daily lives very simple, in a manner that this new way of interacting with virtual objects required almost no adaptation process. As a result, it is unlikely that we will see a difference in performance between controlling animation through mouse clicks and direct touch.

H2: *The TM technique will provide higher accuracy than the traditional animation.*

We based the TM technique on the premise that one can use their proprioceptive sense as a tool for recalling information through muscle memory (i.e. the process of consolidating a motor task into memory through

repetition). Further, the TM technique allows one to start/resume the animation on whatever position of the time picker they judge useful and to animate time forward or backwards as it better meet the ongoing analysis or one's cognitive abilities. We believe that our technique can provide better answers to the analytic tasks than the traditional animation, which is strongly dependent on users' memory, even though it supports control via interactive methods such as play, pause, and resume.

H3: *Users will prefer to use the TM technique rather than the traditional animation.*

There are evidences in the literature showing that physical interaction is more engaging (Arvola and Holm, 2014). Further, the TM technique gives the user full control over time animation, behaving according to their tilting movement. Thereby, we believe that users will found our technique more fun, favoring it over mouse clicks to control animation.

4.4.2 Materials and Methods

Experimental Conditions and Tasks

The experiment follows a completely randomized design to explore the aforementioned assumptions, which experimental conditions correspond to four interaction styles for animating time through the TM technique and the *traditional animation* (TA). They are defined as follows:

- a) the *TM Circular* refers to the rotational tilting movement creating clockwise and counterclockwise curves that allow to place a marker on time units placed over a circular axis. A button is available to play/pause/resume animation via direct touch;
- b) the *TM Linear* refers to a linear tilting movement from left to right and contrariwise that controls a marker on time units placed over a linear axis. A button is available to play/pause/resume animation via direct touch;
- c) the *TA Mouse* refers to the mouse input, which allows to play/pause/resume the animation. The technique works as a movie of 24 frames depicting the presence indicator at each time unit, and selecting particular

time units by directly clicking on the corresponding position on a linear axis; and

- d) the *TA Touch* refers to a tactile input, which operates in a similar way to the previous condition, except that the user plays/pauses/resumes the animation and selects time units by means of direct touch on the buttons and linear axis, respectively.

Following a within-subjects design, we assigned each participant to all experimental conditions and asked them to complete two sets of tasks (Table 4.4.1). Each set contains three tasks regarding either presence density or fluctuation rate indicators. The tasks are elementary regarding the spatial dimension and synoptic with regard to time ($s \rightarrow T \rightarrow M$), and their level of complexity is constant. Each set was applied twice, which difference was the spatial location referred by the tasks.

ID	Set 1-3		Set 2-4	
	Task	Locations ⁱ	Task	Locations
1	Describe the variation of presence density in location X along the day.	3 5	Describe the variation of fluctuation rate in location X along the day.	1 50
2	List the time units when presence density of location X is low .	8 6	List the time intervals when fluctuation rate of location X is negative .	4 56
3	List the time units when presence density of location X is high .	9 4	List the time intervals when fluctuation rate of location X is positive .	7 5

ⁱ One spatial location per set

Table 4.4.1: The sets of analytic tasks applied during the Experiment II.

Apparatus

We used an HP EliteBook 840 g3 Notebook PC, with a 14-inch screen and 1920x1080 pixels resolution, and a Samsung Galaxy Tab S3 tablet with a 9.7-inch screen and 2048x1536 pixels resolution. The laptop served for execute the *TA Mouse* experimental condition and to answer the pre- and post-test questionnaires. The tablet was the basis for the remaining experimental conditions.

Procedure

Considering that the goal of this experiment was to assess an animation interface and different interaction styles through direct identification tasks, we considered irrelevant the users' experience on urban mobility analysis. Therefore, we recruited volunteers through an e-mail list of a Computer Lab. An experimenter guided each individual session, which lasted about 30 minutes. To avoid possible bias introduced by misunderstandings and because the research was conducted in France, we run the experiment, including questionnaires and tasks, in English or French languages, according to the participant's preference.

The session started with the participant reading and signing the Term and Conditions agreement (see Appendix E.3). Secondly, they answered the socio-demographic questionnaire, which additionally to the general information about the participant, included questions regarding any existing medical condition or recurrent pain on their wrists/hands, and whether they are color-blinded (see Appendix E.4). Afterwards the experimenter performed a short presentation and demonstration of the TM technique, and explained the goals and protocol to be followed in the experimental session. During the learning phase, the participant was given a moderate time (i.e. 10 minutes) to freely explore the variation of presence density over time of polling districts defined in the Grenoble's survey. To avoid this contact with the geographical map and indicators to affect the results, we used a territorial partition into intermediate areas during the trial phase.

The trial phase comprised four parts, one per experimental condition (Figure 4.4.1). Each part consisted of completing a set of tasks using one of the experimental conditions, which were counterbalanced using every possible combination. The visual interface embedded a slide-like questionnaire for presenting and answering the tasks, which would automatically set the presence indicator and interaction technique necessary for solving the tasks in each part. This interface would also record the completion time per task and the interactions made for selecting time units and zooming in/out the map view. Alternatively, users could write their answers in an external form displayed on the laptop where they could use a physical keyboard. Since most experimental conditions ran on a tablet, we gave users this choice to prevent the discomfort caused by their possible lack of practice with virtual keyboards.

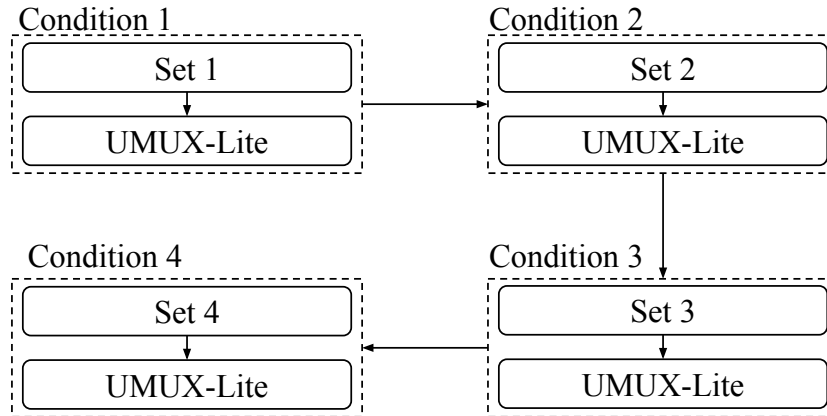


Figure 4.4.1: The protocol followed during the trial phase of Experiment II. The conditions 1-4 are replaced by a counterbalanced order of experimental conditions.

After each experimental condition, we applied the UMUX-Lite questionnaire (see Appendix E.1) to assess usability of the interaction style. Participants could ask for clarifications about the visual and interaction tools and/or the tasks themselves during the whole experiment. The post-test questionnaire gathered information about users preferences over the techniques through a pairwise comparison among the conditions and a rating 4-item scale in each we assessed the satisfaction on using each technique (see Appendix E.2). Finally, we asked participants to share their thoughts on the techniques and the experiment itself.

Participants

Seventeen (17) unpaid persons took part in this experiment (9 females), mostly researchers or PhD students on computer science. They were aged between 23 and 58 years old ($M = 33$, $SD = 11.18$). Three people reported left-handedness, which information was used to place the time picker in a way that the participant could comfortably reach the button for pause/resuming the animation.

Two people reported a medical condition affecting their wrists (i.e. early osteoarthritis and carpal tunnel), and one person reported to recurrently feel pain in their wrists, which information served to check whether a possible difficulty in carrying out the tilting movement affects the results. Everyone self-reported normal or corrected-to-normal vision and not to be color blind.

This would help to determine whether misinterpretations of information from the choropleth maps could be due to preexisting visual impairments or disorders, since we use color hue and intensity to encode information.

4.4.3 Results

Completion Time and Response Accuracy

We did not observe statistical significance among experimental conditions regarding the difference of mean completion times of tasks groups, which average time to finish the whole set of tasks was 5 minutes and 30 seconds. Regardless the experimental condition, we found statistical significance in the difference of mean completion times of the 1st and 3rd tasks (TA Mouse: $p < .01$; others: $p < .001$), showing that users could combine the obtained experience with the interaction and task styles to complete the next task faster (Figure 4.4.2 – left).

Further, we found statistical significance in the difference of mean completion times of the 1st and 2nd tasks when using the TM technique regardless to the movement style (circular: $p < .05$; linear: $p < .01$), while using the TA technique we found statistical significance (90% confidence level) in the difference of mean completion times of the 2nd and 3rd tasks (*TA Mouse*: $p = .053$; *TA Touch*: $p = .098$). The former shows that users could improve their completion times from the 1st to 2nd tasks, which could reflect a smooth learning curve for the TM technique, or the good memory of users, since the 1st task requires them to explore the indicator over every possible time unit and the 2nd/3rd would require them to identify the time units when a given event occurs (e.g. the fluctuation rate is negative). This similarity regarding the type of 2nd and 3rd tasks could also explain the lack of statistical significance with a 95% confidence level between the mean completion times of 2nd and 3rd tasks regardless the experimental condition.

For all experimental conditions taken together, the tasks responses were 76% accurate. Nevertheless, the mean accuracy of results obtained using the *TM Circular* condition was 50% ($SD = .24$), while the remaining interaction styles provided responses which accuracy was over 83% ($M = .84$, $SD = .2$). We found statistical significance regarding the mean scores obtained under the *TM Circular* and every other experimental condition (*TM Circular* – *TA*

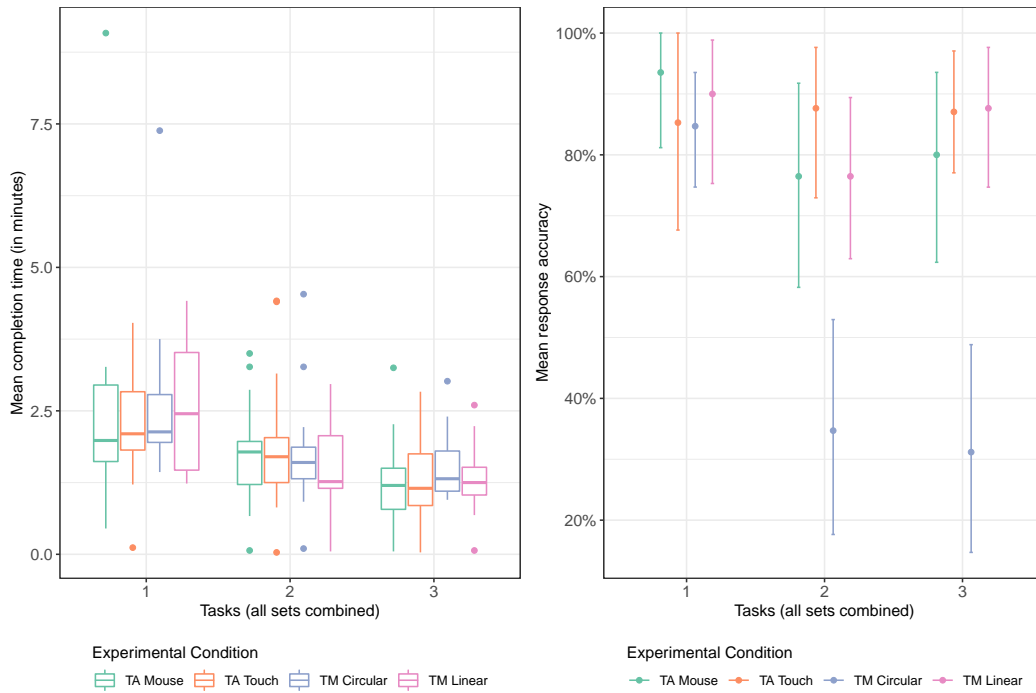


Figure 4.4.2: Mean completion times and response accuracy per task across experimental conditions.

Mouse: $p = .047$; *TM Circular* – *TA Touches*: $p = 0.0062$; *TM Circular* – *TM Linear*: $p = .0182$). The accuracy was similar across tasks for every experimental condition, except for the *TM Circular* (Figure 4.4.2 – right). Regarding the latter, we found statistical significance in the difference of mean response accuracy of 1st and 2nd/3rd tasks ($p < .01$).

Taking all experimental conditions together, users performed around 4 zooming in/out operations to solve the 1st task ($M = 4.69$, $SD = 2.34$), while only 2 operations were necessary to solve the 2nd ($M = 2.37$, $SD = 1.79$) and 3rd ($M = 2.79$, $SD = 2.47$) tasks. This difference was statistically significant between the 1st and 2nd tasks while using the *TM* technique (irrespective to the movement style) and under the *TA Touch* condition ($p < .01$). Further, we observed statistical significance in the difference of means regarding the number of zoom operations necessary to solve the 1st and 3rd tasks while using the *TM Linear* ($p < .05$) and the traditional animation, regardless the interaction style (*TA Touches*: $p < .05$; *TA Mouse*: $p < .01$). These differences could be resulting from a learning curve (of the interface and/or interaction techniques) or from users taking longer to center the map during

the 1st task in a way that every necessary spatial location was clear and readable without further adjustments.

The difference of means in neither zoom in/out operations nor time units selection was statistically significant among experimental conditions. Although a greater number of time units selection would be expected for the 1st task over the remaining, since it required a thorough exploration of the indicator over every possible time unit, we have only found statistical significance between the 1st and 3rd tasks when performing the experiment under the *TA Mouse* condition ($p = .017$).

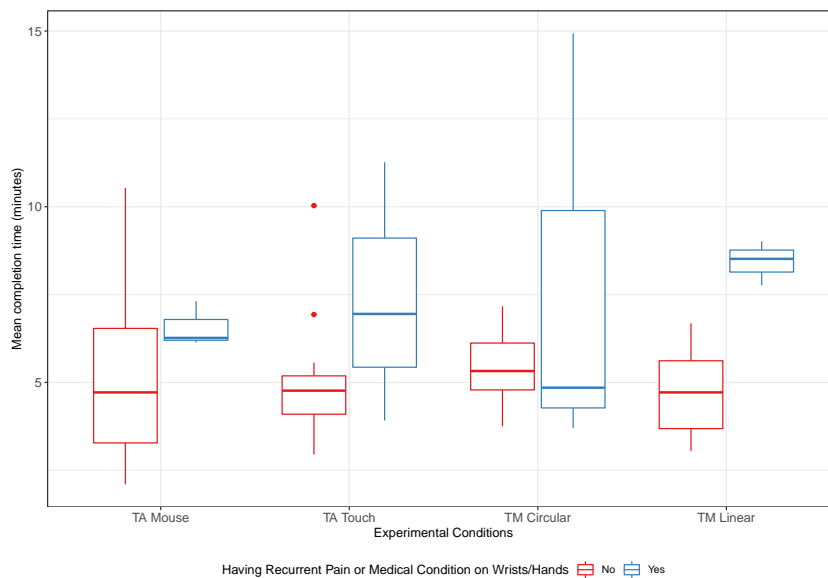


Figure 4.4.3: Comparison of mean completion times per experimental condition between people that reported having recurrent pain or a medical condition involving their wrists/hands (blue) and people without pain in these body regions (red).

Considering a 90% confidence level, we found a positive correlation between the mean amount of time units selection and completion time when using *TA Touch* ($R = .29$, $p = .098$) and the *TM Linear* ($R = .32$, $p = .076$). While more interactions were necessary for completing tasks under the *TA Touch* condition, the longer users took to solve the tasks, the less accurate were the responses ($R = -.48$, $p = .05$). Under this same experimental condition, users who reported higher prior experience with non-conventional interaction techniques seem to have provided more accurate answers to the tasks ($R = .43$, $p = .082$). Finally, under the *TM Circular* condition, older people tend to take longer than younger ones to complete the tasks ($R = .46$, $p = .098$).

The TM technique requires the user to manipulate a physical device by performing a rotational/left to right movement with their hands and wrists to explore the variation of indicators over time, which could affect the experience of people that have recurrent pain or medical conditions involving these body regions (3 persons of our sample). In fact, mean scores suggest that these people took longer to complete the tasks under every experimental condition (Figure 4.4.3), which difference was statistical significant under the *TM Linear* condition ($p < .01$).

Usability and Preference

As a reminder, we applied a two-part preference questionnaire, which consisted of rating a statement that reflects the satisfaction of undertaking each experimental condition and to choose one condition over the other in a pairwise comparison. Considering the satisfaction statement, they enjoyed better the *TA Touch* and the *TA Mouse* conditions (Figure 4.4.4 – top), which was expected since we are accustomed to use direct touch to interact with our smartphones and mouse interaction in computer desktops in our daily routines. Regarding the TM technique, they enjoyed using the *TM Linear* condition, which the great majority of users either “agreed” (4 points) or “strongly agreed” (5 points) with the statement, while the *TM Circular* was strongly disliked.

The pairwise comparison of experimental conditions showed that the *TM Circular* was never chosen against the other conditions (Figure 4.4.4 – bottom). The preference of users regarding the *TM Linear* and the traditional animation irrespective of the interaction input seems to be balanced, since about half of them chose the *TM Linear* over both mouse and touch inputs.

The mean UMUX score of all experimental conditions taken together was 47.3 ($SD=6.65$) from a maximum score of 100 points. Surprisingly, considering the preference of users over the experimental conditions, the *TM Circular* obtained a slightly higher score ($M = 48.7$, $SD = 5.91$) than the remaining conditions ($M=46.8$), which difference did not present statistical significance. Nevertheless, the overall usability of every interaction style is considered absolutely unsatisfactory according to the CGS (see Table 4.2.1), in which the obtained mean scores are within the range of grade F.

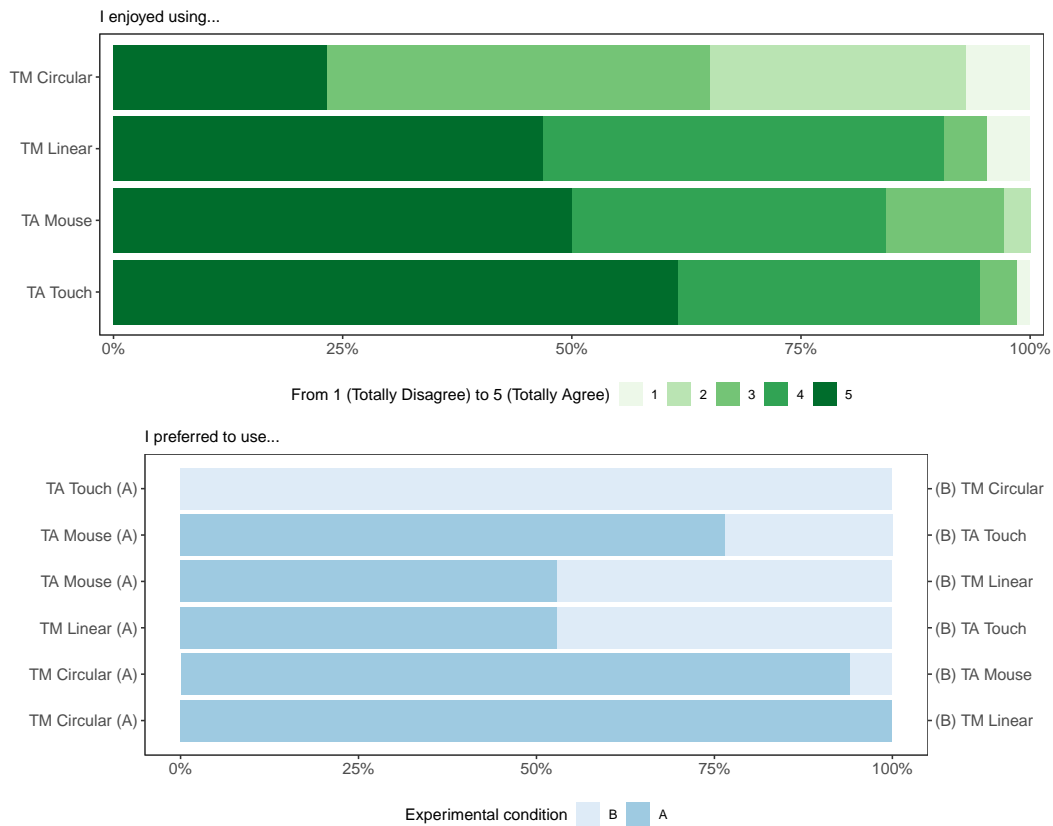


Figure 4.4.4: Participants rating of a statement reflecting the satisfaction of using each interaction style (top) and their choices of one style over the other in a pairwise comparison.

Participants found it difficult to select time units using the circular movement, mostly due to the feeling of performing a non-natural movement, and the size of rectangles, which were too small to accurately place the time marker on them. Further, they found the map sometimes difficult to read. For instance, the diverging colors and the data format (percent) of the fluctuation rate map hindered the indicator interpretation because they could not naturally establish the connection between numbers (proportion of location' population size) and colors (red: increasing; blue: decreasing). Changing the legends according to the selected time unit turned out to be disturbing for some participants, while others would take a long time to realize the legend was changing in the first place.

4.4.4 Synthesis

Hypotheses Assessment

H1: *User performance will be similar whether interacting with traditional animation via mouse clicks or direct touch.*

Under the experimental condition which interaction was via direct touch, we did observe a small positive correlation between the number of time units selection and completion time, which latter seems to be negatively correlated to response accuracy. However, the difference of means of scores and completion time was not statistical significant between these interaction styles, neither was the difference in the number of time units selection and zooming operations. Hence, we **accept** this hypothesis.

H2: *The TM technique will provide higher accuracy than the traditional animation.*

The rotational movement required for controlling the TM technique is harder to perform than the linear one, which combined with the difficulties encountered to place the time marker on a particular time unit, hindered the successful accomplishment of the proposed tasks. In fact, the difference between response accuracy in the circular condition and the remaining was statistically significant dropping from 83% to 50% of correct answers. On a positive note, when completing tasks using the linear movement, the response accuracy and completion time were similar to traditional animation, irrespective to the interaction style. Considering that response accuracy was worse (circular movement) or equivalent (linear) to the traditional animation, we **refuse** this hypothesis. Nevertheless, we could use the TM technique with a linear movement instead of traditional animation without losing performance, since users also considered it easy to use and enjoyable.

H3: *Users will prefer to use the TM technique rather than the traditional animation.*

Similarly to the previous hypothesis, we observed that users did not enjoy using the circular movement for exploring the variation of data over time, and they found it to be frustrating and difficult to use. Nonetheless, participants enjoyed using the linear movement and they even chose it over the traditional animation in our pairwise comparisons. Interact-

ing with the traditional animation by means of direct touch also received a great approval from the participants. Therefore, we **accept** this hypothesis, and consider merging both techniques so the user can animate time using the movement and select particular time units via direct touch.

This experiment aimed to test whether the TM technique could provide better user performance than the traditional animation. Participants underwent a within-subjects design with four experimental conditions. We asked them to answer a set of three tasks (synoptic with regard to time and elementary regarding the space dimension) under each condition, i.e. animating time through the TM technique controlled by a circular and linear movements, and the traditional animation controlled by means of mouse clicks and direct touch. This configuration allowed us to investigate whether and how each interaction style affects the user performance while exploring the variation of presence indicators represented through choropleth maps.

Our results suggest that the TM technique would have to be significantly improved for allowing one to achieve performance through a rotational tilting movement. These improvements would regard not only the physical interaction, i.e. reducing the movement sensibility, but specially the visual representation. We have chosen to place the circular axis on the screen's bottom (either left or right), using 25% of the window's height, which appeared to be appropriate since the map must be visible during the whole time the animation is enabled to allow map reading (see Figure 4.3.3). However, as reported by users, this choice turned out to be uncomfortable for placing the time marker on the rectangles, which were excessively small for achieving precision.

The difficulty for selecting particular time units could explain the radical drop of response accuracy from the 1st task of each set to the 2nd and 3rd. The latter two tasks required users to identify the time units when a certain event happened (e.g. presence density increase), which require them to pause the animation over certain time units for verifying the information. The first task would be easier to accomplish, since it consisted of describing the general behavior of presence density/fluctuation rate indicators for a given spatial location, hence reducing the “pause/resume” operations.

On a positive note, the TM technique could replace the traditional animation (regardless the interaction style) without performance loss, since response

accuracy and completion time were similar among them. Participants equally enjoyed using the linear tilting movement, mouse clicks and direct touch for controlling time animation.

We believe our system can benefit from combining the linear movement with direct touches, which would help users to animate time with greater flexibility while selecting particular time units via direct touch. In the following, we report the user experiment performed to evaluate the re-designed visual and interaction tools (i.e. *eSTIME2.0*), which uses this improved version of TM technique for animating time.

4.5 Experiment III: eSTIME v2.0

This experiment aims to evaluate the usability of a redesigned version of our prototype, called eSTIME v2.0. We have made significantly changes on the visual and interaction tools to provide a better experience to our prospect users, while achieving effectiveness and efficiency to solve domain-related tasks. Our main goal was to investigate the usability of the visual and interactive tools to assist the analysis of human mobility patterns through the exploration and comparison of diverse indicators over multiple spatio-temporal granularity levels.

Regarding the represented data, this prototype does not include yet indicators describing the daily trajectories of individuals, neither thematic information describing trip purposes or activities. Likewise the first experiment, this prototype allows the analysis of population presence dynamics throughout the territory, travel flows and trips, which latter are described by used transportation modes.

Users provided satisfactory answers to the proposed questions in the first experiment, yet their response time was longer than desirable for everyday use and they reported high workload scores. The interface lacked on intuitiveness, specially regarding interaction with dashboards. For reminder, a four-step process was necessary to visualize an indicator: choose the territorial partition, one or many indicators, the analytical dashboard where to display it and submit the choices, which would result on displaying each visualization on the leftmost blank window of the selected dashboard, which re-assorted the views/indicators each time the user deleted or added some-

thing. In the following we describe the modifications we made in order to improve the intuitiveness and, therefore, the usability of our prototype.

4.5.1 Visual and Interaction Tools

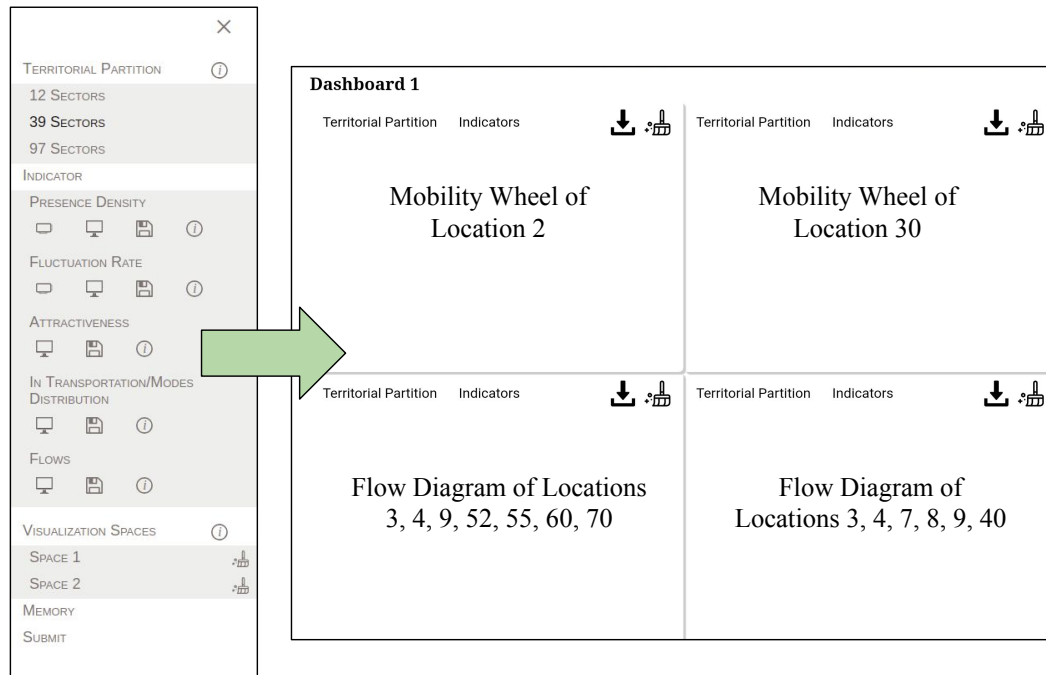


Figure 4.5.1: The menu interface was re-designed using the slideshow metaphor, which slides represent the dashboards and the four sections allow to directly choose where to visualize indicator, controlling the arrangement of visualizations on each dashboard.

To improve intuitiveness, we re-designed the menu following a slideshow metaphor, which slides correspond to dashboards. Each slide is cut into four sections to represent the layout in four windows of the dashboard, allowing the user to directly control the arrangement of visualizations (Figure 4.5.1). The user would interact directly on a section within the slide corresponding to the dashboard of their preference where the visualization ought to be displayed. Each section contains two drop-down lists, which allow the user to choose the territorial partition and the indicator, which automatically applies changes on the dashboard, i.e. display the visualization, replacing the current one in that window, if necessary. The top right corner of each section contains two icons for saving the visualizations as a *png* image, and for clearing a window of the dashboard (i.e. delete the visualization), respectively.

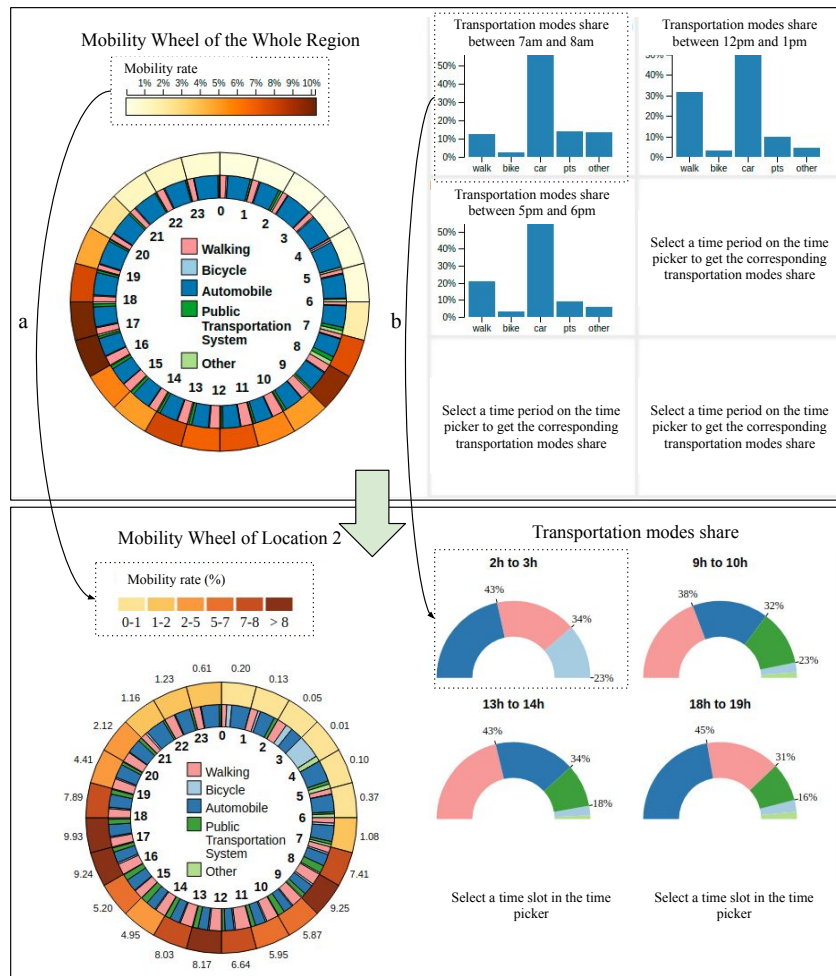


Figure 4.5.2: The modifications made to the Mobility Wheel. (a) We used the *Jenks* natural breaks classification method to better represent the mobility rate values, which also reflects in more comprehensible color code and legend. (b) The bar charts were replaced by arcs, which leverage the same color code of the Mobility Wheel to represent transportation modes.

During the first trial of eSTIME, the users reported having trouble to interpret the information displayed by the Mobility Wheel, which led us to make two main modifications to the chart. Firstly, considering the difficulty to interpret the mobility rate values encoded by color intensity on the outermost ring of the Mobility Wheel, we re-classified the range of values using Jenks natural breaks method, which determines the best arrangement of values into different classes. This way we could better represent the similar and different mobility rate between time units, while reflecting in a more comprehensible color code and, consequently, a clearer legend (Figure 4.5.2a). Further, to

allow for an accurate reading of the chart, we included the actual mobility rate value at the side of each time unit.

For a reminder, we represented the transportation modes share per time period through tiled bar charts next to the Mobility Wheel. This representation turned out to be unsatisfactory for comparing the transportation mode share across time units due to the y -axis changing according to the maximum value of each group. Moreover, the modes were identified via a code on the x -axis, which could cause confusion. We replaced the bars into arc charts (Figure 4.5.2b), identifying modes through the same color code as the one used in the innermost ring of the wheel, which accelerate the assimilation of information.

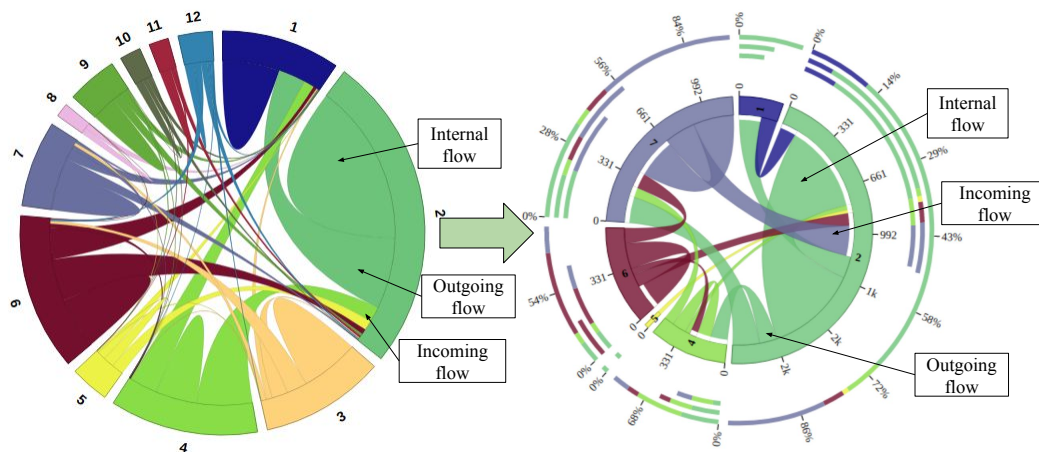


Figure 4.5.3: The modifications made to the Flows Diagram. A white gap has been drawn between arcs and ribbons to indicate incoming flows, and three peripheral bars present aggregate information about general, incoming and outgoing flows for each location.

Previously, travel flows between pairs of locations were represented through a simple chord diagram, which ribbons color and thickness were the only indication of flows direction and volume. This simplicity turned out to be a barrier to effectively transfer the information. Therefore, we upgraded the diagram into a more legible and intuitive visualization, following the layout used by Shi et al. (2018) (Figure 4.5.3). Further to the ribbons color to encode the flow origin, we added a white gap between each arc and ribbons to encode incoming flows. We represent the internal flow to a spatial location as a ribbon that starts and ends on the same arc. Three peripheral bars placed externally to the diagram represent aggregate information on flows for each spatial location, which color encodes the locations with which they

have flows exchanges. The outermost bar presents the total proportion of flows being exchanged with the corresponding location (regardless the direction and including internal flows), and the middle and innermost bars represent the proportion of outgoing and incoming flows to/from the remaining locations, respectively. Adjacently to the arcs, we included information on the amount of trips that location is responsible for, which gives a better picture of that location's influence within the group.

According to the outcomes of experiment II (see Section 4.4), we used the TM technique with a linear tilting movement for animating time and allow the selection of particular time units by means of direct touch on a timeline. The latter has two roles: (1) selecting time units, and (2) opening the arc charts next to a mobility wheel, which should be enabled on a checkbox determining the current role of the time picker. The latter is a two-step process: choose the chart (spatial location) where to apply the modifications on a list next to the timeline, and select the time unit to which display the indicator of transportation modes share. We colored the rectangles composing the timeline in red to indicate that an arc chart for that time unit (and spatial location) is already being displayed.

To avoid confusion while reading the maps of presence density and fluctuation rate due to changing the legends at each time unit, we adopted a single legend and a color scale defined by the minimum and maximum possible values within the indicator's measures for all time units combined. The map displayed on the Control Unit has two roles: (1) pan & zoom this and other maps, and (2) interact with the flows diagrams by selecting spatial locations that highlight the incoming, outgoing and internal flows regarding that location. Similar to the double function of the timeline, these should be enabled via a checkbox that indicates the current function of the map.

4.5.2 Hypotheses

In this experiment, the overarching hypothesis is that the improvements made on our prototype can enable users to solve domain-related tasks effectively and efficiently while feeling comfortable using our interface. On a more particular level, we investigate the following hypotheses:

H1: *Users will be able to efficiently explore the indicators to solve domain-related tasks.*

The outcomes of our first experiment showed that users could achieve a response accuracy of around 80% despite the unsatisfactory usability and the high workload scores. Nevertheless, the price for such response accuracy was a long exploration time, which is undesirable for a regular use of the tool. We believe that the improvements we made in our visual and interactive tools will allow users to achieve a better or equivalent response accuracy within a satisfactory exploration time.

H2: *Users will feel comfortable using eSTIME.*

The former layout of menu(s) for visualizing and modifying indicators turned out to be confusing for participants, since it was not clear what and where something would be displayed. Rearranging the visualizations without users' consent could cause them to lose their track of thought since their spatial memory of before the change would be incoherent with the new spatial arrangement. Moreover, as pointed out for some users (particularly the ones with some knowledge on the domain), it would be more intuitive to firstly choose the visualization and then the spatial location for which explore the indicator, which is possible in the present version of eSTIME. We believe that this intuitiveness added by the straightforwardness of indicators exploration will make users comfortable while using the tool to solve the domain-related tasks.

4.5.3 Materials and Methods

Participants

Twenty-four (24) unpaid persons took part in this experiment (8 females). Two of them did not finish the trial in time and we lost the log files of a third one. Thus, we considered the data from twenty-one (21) participants to assess our hypotheses. The volunteers were all master students on geography aged from 21 to 28 years old ($M = 22.71$). Particularly, they were following a class focused on the representation of territorial dynamics that is part of the Master's degree GAED (*Master en géographie, aménagement, environnement et développement*, in French)².

Everyone reported to have normal or corrected-to-normal vision, and not to be color blind. This would help to determine whether misinterpretations

²Course M1 MOBAT, see <https://master-gaed.univ-grenoble-alpes.fr/7-parcours/m1-m2-mobat/parcours-mobat-m1-m2--412604.kjsp?RH=3987605545251016>

of information from the charts could be due to preexisting visual impairments or disorders, since we encode information through color hue and intensity.

Procedure

From our first experiment, we recognized the necessity of allowing users to use the visualization environment for a longer time to master the visual and interactive tools before beginning the trial. Therefore, we ran this experiment in two moments. The first moment comprised two 3-hours sessions in which users worked in pairs to complete a set of exploratory tasks regarding indicators of travel flows, population and territory dynamics using eSTIMe. These sessions intended to accustom users with the interface, while confirming the adaptability of the prototype for solving domain-related tasks. We followed a relaxed format to avoid pressuring the participants, which could affect their experience. The sessions were accompanied by three experimenters who would answer any question they had regarding thematic and interactive aspect of eSTIMe.

For a technical matter (availability of tablets for everyone at the same time), the learning phase was performed using two conventional desktop displays, one being the Control Unit and the other holding an analytical dashboard. The TM technique is a component for animating time, which does not affect the learning of remaining components to visualize and interact with indicators, since mouse interaction can handle the remaining interactions.

The trial happened two weeks after the learning phase and comprised two collective sessions, in which twelve participants were in the same room working individually for completing a set of analytic tasks. Three experimenters accompanied the sessions, which lasted around one hour each. The session started with the participant reading and signing the Term and Conditions agreement (see Appendix F.2). Secondly, they answered the socio-demographic questionnaire (see Appendix F.3). Afterwards the experimenters reminded participants about the available mobility indicators and visualizations. They also made a short demonstration of the TM technique, which would be later tried by the participants in a short training phase before completing the analytic tasks.

Participants were provided with a sheet of paper where they should write down the solution for each task. A questionnaire interface embedded into

the prototype would present the tasks description one after the other, which gathered the completion time and interactions (i.e. time units selection, zoom in/out, and opening views) performed to answer each task. They had 16 training tasks to help them to remember how to use the interface (e.g., visualize the presence density indicator) and to practice the linear tilting movement for animating time through the TM technique (e.g., tilt the tablet from left to right and contrariwise, placing the marker over different time units).

The post-test questionnaire gathered the subjective usability of eSTIME and perceived workload. The latter was measured through a reduced version of the NASA TLX questionnaire, known as Raw TLX (RTLX) (Hart, 2006), which eliminates the weighting process all together, and keeps only the ratings of sub-scales, allowing for measures as sensitive as the original format. We establish the scores of sub-scales as the averaged ratings times 10, and the general score as the average of sub-scales' scores. Finally, to evaluate the differences of apparatus in the learning and trial phases, we asked users whether they prefer using the tablet or a second desktop monitor as Control Unit. We also gathered their opinion about the visual and interactive tools, and the experiment itself.

Tasks

During the learning phase we asked participants to complete three sets of tasks regarding the analysis of two objects of interest (see Appendix F.1), making a total of twelve tasks. The first set had five tasks regarding the dynamics of population presence over the territory. The second set contained four tasks regarding the variation of travel flows and trips over the day. Finally, the third set had three tasks regarding a cross analysis of travel flows, trips, population and territory. These tasks were mainly synoptic, requiring the user to explore different indicators over space and time to understand their spatial distribution and temporal variation. Since users were working in pairs and could use eSTIME during six hours, we use this learning time to understand whether the system was ready to assist the solving of complex tasks.

In the trial phase we asked participants to complete a set of 14 analytic tasks, which were simpler than the previous ones to ensure feasibility within the time available to accomplish the experiment (Table 4.5.1). The tasks covered the spatio-temporal variation of indicators describing presence density, fluctuation rate, attractiveness, mobility rate, transportation modes share,

	Type	Task Description
1	$s \rightarrow T \rightarrow M$	Identify whether the measures of presence density of location X^i varies along the day. In a positive case, identify the time unit when this indicator has the highest measure.
2	$s \rightarrow T \rightarrow M$	Identify whether the measures of fluctuation rate in location X varies along the day. In a positive case, identify the time unit when the indicator has the highest measure.
3	$t \rightarrow S \rightarrow M$	Over 24 hours, identify whether the adjacent neighbors to location X have the same measure of presence density . In a negative case, identify the different measures of presence density for those neighbors.
4	$t \rightarrow S \rightarrow M$	Over 24 hours, identify whether the adjacent neighbors to location X have the same measure of fluctuation rate . In a negative case, identify the different measures of fluctuation rate for those neighbors.
5	$s \rightarrow T \rightarrow M$	Identify the time intervals when the mobility rate of location X is the highest.
6	$t \rightarrow s \rightarrow M$	Over 24 hours, identify the three most used transportation means to reach location X
7	$T \rightarrow s \rightarrow M$	Identify the most used transportation modes during the one or two time units when the mobility rate of location X is the highest .
8	$T \rightarrow s \rightarrow M$	Identify the most used transportation modes during the one or two time units when the mobility rate of location X is the lowest .
9	$t \rightarrow S \rightarrow M$	Identify whether location X is attractive regarding the remaining locations within the territory.
10	$t \rightarrow S \rightarrow M$	Identify whether location X is more or less attractive than its neighboring locations.
11	$t \rightarrow s \rightarrow M$	Identify where the incoming flows of location X are from.
12	$t \rightarrow s \rightarrow M$	Identify where the most important incoming flow of location X is from.
13	$t \rightarrow s \rightarrow M$	Identify where the outgoing flows of location X are directed to.
14	$t \rightarrow s \rightarrow M$	Identify where the most important outgoing flow from location X is directed to.

ⁱ The X is randomly replaced by one of the following spatial locations: 5, 7, 31, 52

Table 4.5.1: Set of tasks used during the trial phase of Experiment III.

and travel flows. Considering the natural difference of geographical and social characteristics of spatial locations, which may affect the measure of indicators, we applied the tasks on different locations (i.e. 5, 7, 31 and 52), which were randomly distributed among participants to avoid the bias of completing every task regarding the same location. Therefore, the set of tasks could be elementary on space (focusing on one spatial location $s \in S$) and synoptic regarding time (focusing on a set of time units T), or elementary on time (focusing on a time unit $t \in T$) and synoptic regarding space (focusing on a set of spatial locations S), or even elementary regarding both space and time dimensions.

Apparatus

In the learning phase, participants used a 24-inch monitor to display the analytical dashboard and a second PC monitor, which characteristics are negligible, to display the Control Unit interface. During the trial phase, the Control Unit ran either on a 10.5-inch Galaxy Tab S (10 devices) or a 9.7-inch Galaxy Tab S3 (2 devices), and the dashboard ran on a 24-inch monitor (Figure 4.5.4).

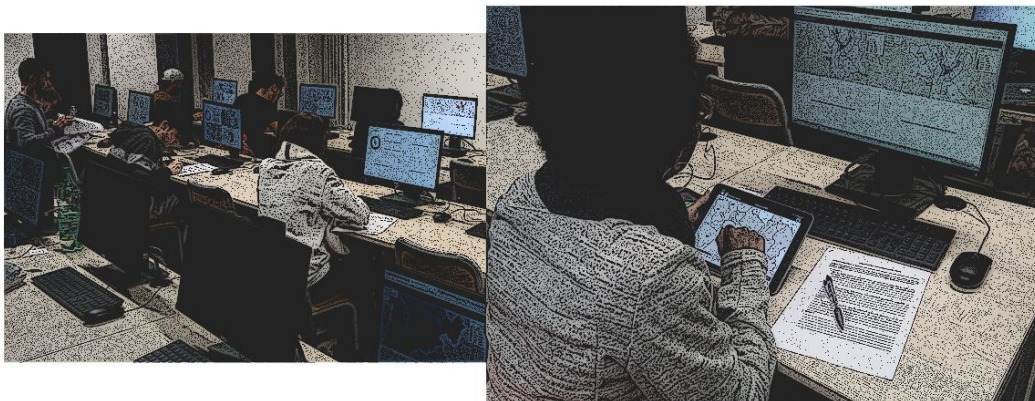


Figure 4.5.4: The apparatus and setup of Experiment III. Twelve participants undertook the experiment simultaneously in a class-like environment.

4.5.4 Results

Completion Time and Response Accuracy

The overall response accuracy was 81% ($SD = .34$), which we noticed to be different depending on the spatial location under analysis. We found statistical significance in the difference of mean scores for tasks regarding the spatial location 52, which average response accuracy was 66% ($SD = .43$), and the remaining locations ($52 - 7: p < .001$; $52 - 31: p < .05$; $52 - 5: p = .056$), which mean response accuracy was 85% ($SD = .3$). These results show that participants could provide less accurate answers for tasks regarding location 52 than 7 and 31 (95% confidence level), and 5 (90% confidence level). Figure 4.5.5 (left) shows that the difference of response accuracy was higher for tasks regarding the attractiveness and presence density indicators, which suggest the reason for this difference could have been caused by map reading issues.

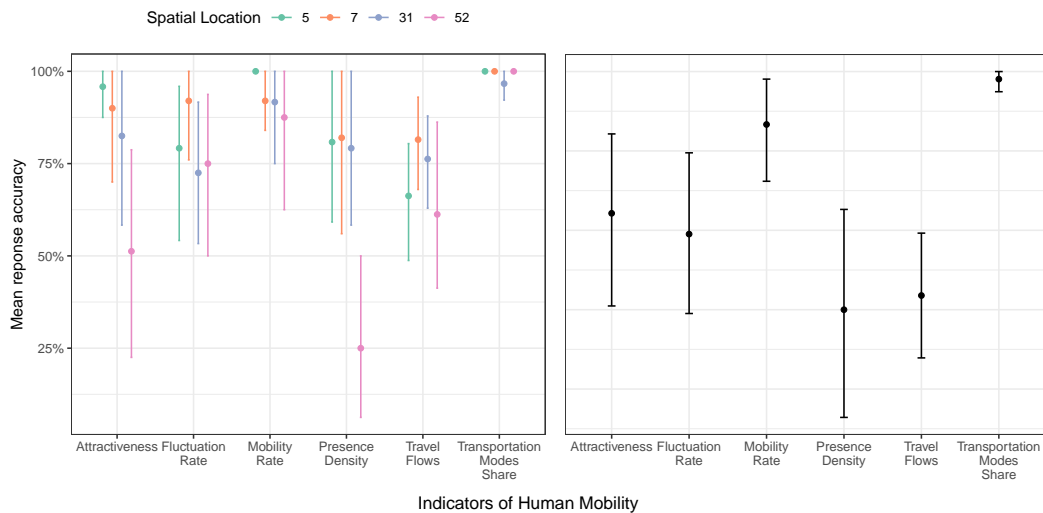


Figure 4.5.5: Average response accuracy per indicator (right) and spatial location under analysis (left).

Regardless the spatial locations under analysis, we found statistical significance in the difference of mean response accuracy between certain indicators (Figure 4.5.5 – right). Overall, the tasks regarding transportation modes share had the most accurate answers, while the ones about presence density had the less accurate answers. Particularly, mean scores of the latter were significantly lower than mobility rate ($p = .081 - 90\%$ confidence level) and transportation

modes share ($p < .001$). The accuracy of tasks regarding the latter indicator were also significantly higher than the fluctuation rate ($p < .05$) and attractiveness ($p = .097$ – 90% confidence level). These differences could be a consequence of exploring the variation of presence density and fluctuation rate over time, which requires reading and comparing several maps, while the information regarding mobility rate and transportation modes share could be extracted from the interpretation of a single chart, without mandatory interaction. Perhaps for the same reason, the response accuracy for these tasks were also higher than for tasks regarding travel flows (mobility rate: $p = .074$; transportation modes share: $p < .001$), which measures could be tough to interpret when the flow exchange between a pair of locations is low reflecting the ribbon's thickness and, consequently, on the extraction of precise information.

The mean completion time for the whole set of tasks was 35 minutes ($SD = 12.9$), with a mean completion time per task of 2.49 minutes ($SD = 2.26$). Similarly to response accuracy, we found statistical significance in the difference of mean completion time for tasks regarding different indicators. Figure 4.5.6 shows that the mean time for completing tasks about presence density ($M = 4.46$, $SD = 2.61$) and fluctuation rate ($M = 3.62$, $SD = 2.73$) was longer than to complete tasks regarding the remaining indicators. We found statistical significance in the difference of completion times between these indicators and attractiveness ($p < .001$), travel flows ($p < .001$), and transportation modes share ($p < .001$). Users also took a significantly longer time to complete presence density-related tasks than the ones regarding mobility rate ($p < .01$).

These differences in mean completion times may be explained by the necessity of exploring the presence density and fluctuation indicators over every possible time unit in order to describe its overall behavior along the day, which could understandably take longer than interpreting a single chart with (i.e. travel flows) or without (i.e. attractiveness) further interaction. We support this hypothesis via the statistical significance found in the difference of time units selections made to answer tasks about presence density ($M = 53$, $SD = 57.3$) and fluctuation rate ($M = 39.5$, $SD = 42.8$), and all other indicators ($p < .001$), which together required less than 2 selections of time units ($M = 1.69$, $SD = 8.71$). We also found statistical significance in the difference of zoom in/out operations necessary to complete tasks regarding presence density ($M = 6.71$, $SD = 9.26$) and fluctuation rate ($M = 3.26$, $SD = 4.94$), with $p < .05$, and the remaining indicators ($M = 1.47$, $SD = 3.95$) with $p < .001$.

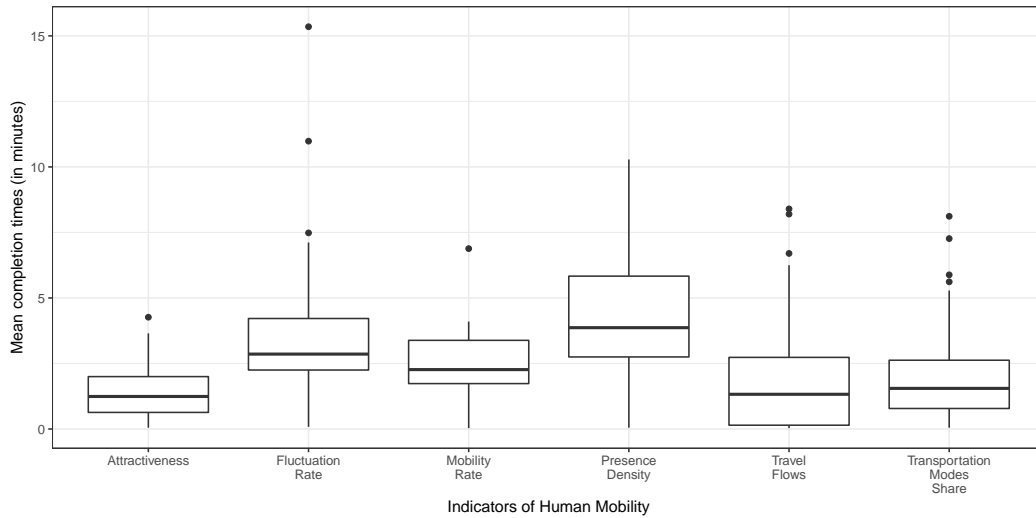


Figure 4.5.6: Mean completion times of tasks regarding each indicator.

Usability

The mean score of the SUS questionnaire was 69.9 ($SD = 13.6$), which corresponds to a grade C in the CGS (see Table 4.2.1). This means the assessed usability of eSTIME is satisfactory, which mean score increased 11.6 points from the first experiment, suggesting the improvements positively affected the overall usability of our prototype.

Overall, participants enjoyed using the tablet as a second screen ($M = 3.95$ in a 5-points Likert scale, $SD = 1.43$) and preferred using it as Control Unit rather than a second desktop monitor ($M = 4$, $SD = 1.22$). Users declared that it was easier to complete the task when they could display visualizations on the desktop monitor and directly interact on the tablet screen, which allowed them to “focus their attention on a single display”. One participant felt that “the physical efforts previously made for manipulating the mouse reduced when using the tablet”. On another note, the few users who disagreed with the statement, appear to prefer a second desktop screen because of the mouse interaction, which they claim to be “more intuitive than the tactile and tangible (TM technique) input” we provide.

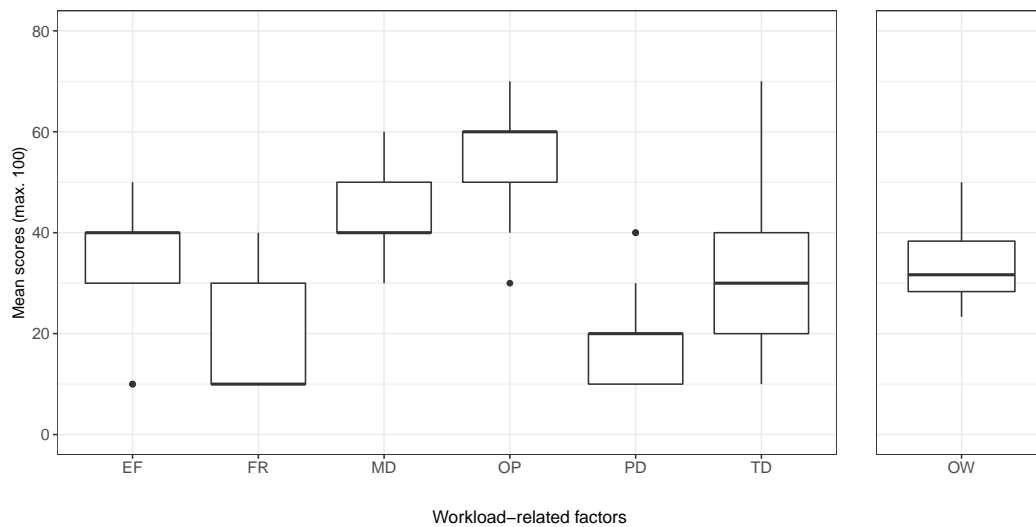


Figure 4.5.7: Mean scores of RTLX for each workload-related factor and overall workload score.

Workload

The mean score of overall workload (OW) was 33.3 points ($SD = 6.8$) over a maximum scoring of 100, which is 30 points lower than the reported workload scores during the first experiment.

Figure 4.5.7 presents the mean scores for each workload-related factor. Overall, participants highly scored their own performance (OP), which difference of mean scores regarding the remaining sub-scales, except the mental demand (MD), was statistical significant (OP – EF: $p < .05$; OP - remaining: $p < .001$). The second main source of workload was MD, which mean scores were higher than physical demand (PD) and frustration (FR) with statistical significance of $p < .001$.

The FR factor does not appear to affect the workload, which mean scores were the lowest among all factors, which difference was statistical significant in comparison to PD ($p < .001$), effort (EF) ($p < .05$) and temporal demand (TD) ($p < .001$). Despite this difference between FR and PD scores, the latter were considerably low regarding the remaining sub-scales, which differences were statistically significant in comparison to MD, PD and EF ($p < .05$). Nevertheless, the perceived physical demand is 50% correlated with the overall workload ($p < .01$), indicating that despite the low scores, this sub-scale affected the way users perceive how hard they had to work in order to ac-

compish the task. Similarly, OW has a 58% correlation with TD ($p < .001$), which is understandable since we had to establish a time limit of one hour and 30 minutes to finish the experiment according to students' time schedule.

In general, users self-reported to have a fair prior knowledge regarding the human mobility patterns within the studied region ($M = 2.95$, $SD = 1$), which is expected since they were following a class on the subject before undertaking the experiment. This prior knowledge is 49% correlated with OP ($p < .01$), suggesting that they might have perceived a high quality on their performance based on their own prior knowledge instead of the process of completing the tasks, since we did not observe any correlation between OP and response accuracy neither completion time.

4.5.5 Synthesis

Hypotheses Assessment

H1: *Users will be able to efficiently explore the indicators to solve domain-related tasks.*

Participants were able to complete fourteen tasks regarding six indicators describing travel flows and presence dynamics in about 35 minutes and providing 81% of accuracy in the responses. The differences we observed in completion time for tasks regarding presence density and fluctuation rate indicators are consistent with the amount of work required to interpret the data representations. Further the number of operations for zooming in/out and selecting time units are equally consistent with the visualization and expected interactions imposed by the task. Therefore, we **accept** this hypothesis since the users understood how to properly use the visual and interaction tools to quickly complete the different tasks. It is relevant to remark that we did not provide a step-by-step support for completing tasks as we did in the first experiment, but we rather left them apply the knowledge acquired during the learning phase.

H2: *Users will feel comfortable using eSTIME.*

While the assessed usability of eSTIME increased 10 points after the modifications made to the visual and interactive tools, the overall workload reduced 20 points. Mental demand was still considered the main source of workload, which is probably a consequence of handling mul-

multiple visualizations to explore different indicators over space, time and thematic attributes. The temporal demand was directly correlated to the perceived overall workload due to the time limit we imposed to fit the experiment in the users' schedule. Nevertheless, users could still perceive their own performance as of high quality. Based on the satisfactory usability score, low overall workload and users' feeling of achievement, we **accept** this hypothesis.

Overall, the assessed usability and the perceived workload scores were satisfactory, showing that our modifications improved the user experience. The prolonged time taken for the learning phase allowed users to properly apply the knowledge acquired regarding the visual and interaction tools two weeks later for completing a set of tasks with only a short reminder of the interface main functions. One participant specifically said that "once we master the visual and interaction tools, it is easy and quick to complete the tasks, even though the interface seems complex at a first glance".

The learning phase allowed us to identify necessary improvements, such as to change back the representation of internal flows to a half circle, since the current format turned out to be confusing for users who could not understand why the flow started as an outgoing flow and finished as an incoming flow, when the flow actually never left the location. Another observation of participants regards the necessity of visualizing the same indicator for different time units side-by-side, not only through animation.

For reminding, both the map and timeline were equipped with a "switch" button that enabled users to choose whether selecting a location on the map would trigger the details on presence indicators or affect the chord diagram, highlighting the ribbons connected to that location, and whether choosing a time unit would open an arc chart next to a Mobility Wheel visualization or affect every indicator according to that time unit. During the learning phase, we observed that users had difficulty remembering to set the current role of the map and the timeline before interacting, which would result on a different outcome than the one they expected. A participant specifically reported after the trial phase that he "could not distinguish the different functions, neither their relevance".

The absence of direct interaction with charts on the dashboard was again reported by participants as necessary to improve the data exploration, which indicates that we should improve the interactive tools to increase intuitiveness.

Participants also said that the flow diagram should be more legible, such as allowing zooming in/out the visualization. We also observed that participants would visualize maps mostly on the dashboard, even though they were conceived to be explored on the tablet where we believe is easier to follow the changes resulting from animation. This behavior could be a consequence of teaching them how to use the visual and interactive tools without the tablet during the learning phase.

Although improvements are still necessary, this experiment allowed us to validate our visualization approach, showing that one can learn the visual and interactive tools, and use them to resolve domain-related tasks. Therefore, the next step in this research is to apply the improvements suggestions and complete the environment to allow the analysis of urban mobility data at the population and individual levels by including the description of travel flows and population dynamics through trip purposes and activities, and the analysis of individual daily activity schedules. The next section describes the usage study conducted with experts on the domain to evaluate this complete version of eSTIME (i.e. *eSTIME3.0*).

4.6 Experiment IV: Experts Feedback

This experiment aims to evaluate the usefulness of eSTIME among our potential users, i.e. professionals working with human mobility at a daily basis either within academic research or urban policies for decision-making on transportation offers, urban planning, and overall mobility issues. Based on the feedback obtained during previous experiments, we modified some relevant aspects of the visual and interactive tools in order to increase intuitiveness and improve their interpretation. We extended the set of visualizations to include the missing indicators that describe travel flows and population presence according to different activities, transportation modes and trip purposes, and the typology of daily trajectories. Additionally, we included the remaining datasets to enable the analysis and comparison of different population mobility patterns within the great regions of Grenoble, Lyon and Rennes metropolitan areas.

4.6.1 Visual and Interaction Tools

The visual and interaction tools used in this experiment are the ones presented in Section 3.5, which correspond to our final prototype. Further to extending the set of visualizations to represent the remaining indicators (i.e. travel flows, trips and presence per activity, trip purpose, and transportation mode, and the typology of activity patterns), we improved the existing visualizations and interaction mechanisms.

The main modifications affected the interactive mechanisms linked to the Control Unit. Firstly, we removed the concept of “roles” linked to the map and time picker, since it was confusing for users. Instead, the selection of spatial locations and/or time units automatically affect every chart which displayed indicator are disaggregate on space and/or time. Likewise, spatial selection and pan & zoom operations function simultaneously, and can be disabled/enabled in each chart by freezing space and zoom, respectively, as the user deems necessary. The action of freezing time rose from the necessity expressed by users for visualizing an indicator on a particular time unit while animating the remaining, which was extended to space dimension and pan & zoom operations. The former works on flow diagrams, where one can freeze the selected ribbons for different spatial locations on various diagrams for comparing them via juxtaposing.

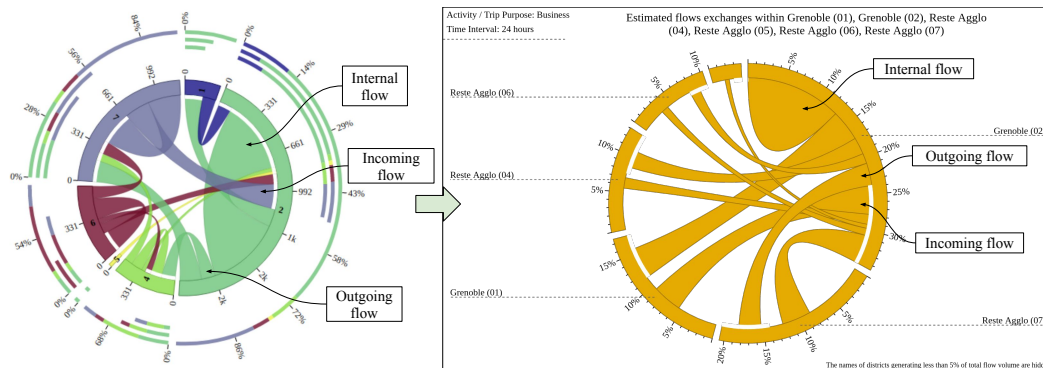


Figure 4.6.1: The modifications applied to the Flow Diagram.

The flow diagrams were modified to represent travel flows generated for different trip purposes and transportation modes. Respecting our uniformity principle, while making visual comparison easier, we decided to color the whole diagram according to the represented trip purpose or transportation mode (Figure 4.6.1). Further, we removed the peripheral bars since it would be impossible to represent the percentage of incoming and outgoing flow through

color coding. Instead, we included a details panel (which currently exists for every chart) that presents information about the actual number of trips represented by the ribbons' thickness, and the proportion of outgoing, incoming and internal trips.

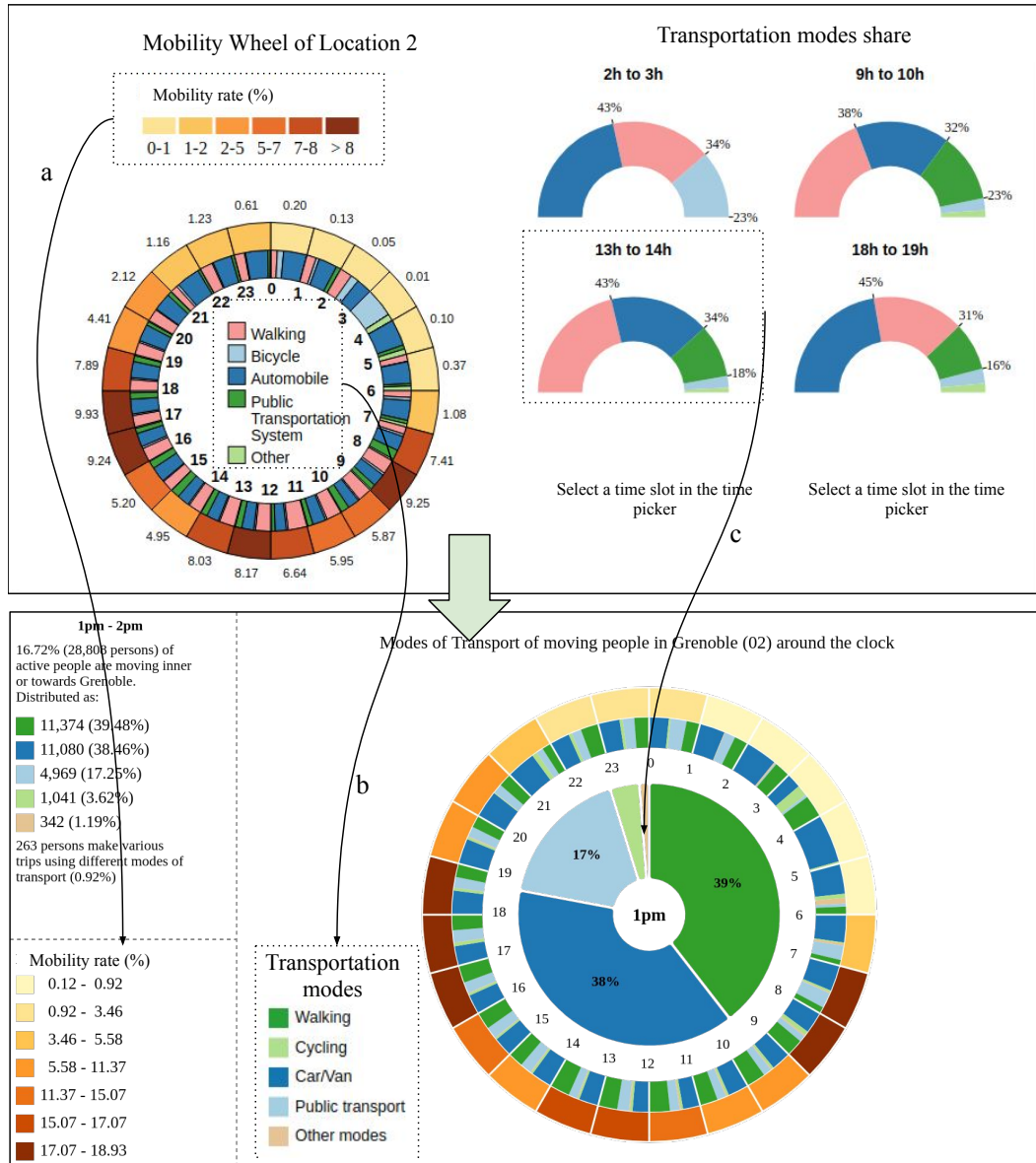


Figure 4.6.2: The modifications applied to the Mobility Wheel.

The first modifications carried out on the Mobility Wheel concern the legends. We improved the legibility of the one for interpreting the mobility rate ranges (Figure 4.6.2 – a), while the one listing transportation modes/trip purposes was moved out of the chart to integrate a shared space in the dashboard

dedicated to the legends listing thematic attributes, once the color code is shared by all charts (Figure 4.6.2 – b, the legend was manually included back in the chart for illustration purposes). Instead, we included a pie chart at the wheel’s center, which gives the transportation modes/trip purposes share aggregate over 24 hours or per time unit through animation (Figure 4.6.2 – c). Hence, the second role previously used for opening arc charts next to the wheel is no longer necessary. Instead if one needs to compare the attribute share indicator over different time units using an enlarged view, they can use the time freezing technique, opening several charts side-by-side each one frozen on a different time unit.

4.6.2 Hypothesis

This experiment explores the following hypothesis

H1: *experts will appreciate our visualization environment to explore daily mobility data.*

The previous experiments allowed us to identify the major issues that damage user experience, which consequently reduces assessed usability and increases workload. The outcomes of experiment III were satisfactory as for increasing usability and considerably reducing overall workload. Further, our observations and participants’ feedback could be applied for improving the existing visualizations and for designing new ones to represent the remaining indicators of daily human mobility. Therefore, we believe to have been able to complete our prototype in terms of the analysis it supports, while providing a satisfactory user experience that have been validated by previous users.

4.6.3 Materials and Methods

Participants

Eight professionals working on different aspects of urban planning took part in this experiment. Four of them were academic researchers, which research focus on diverse aspects of human mobility. Two people are head of studies

within the *Syndicat Mixte des Mobilités de l'Aire Grenobloise (SMMAG)* responsible for analyzing and developing forward looking strategies regarding transportation solutions within the Grenoble urban area. Another two professionals are head of studies within the urban planning agency responsible for developing expert assessments regarding the various domains of urban planning and territorial development (e.g., planning, housing, mobility, economy, environment, real estate) of Grenoble urban area.

One participant could not finish the experiment for personal reasons. Thus, we considered data generated from 7 participants (4 female) to assess the usefulness and user experience of eSTIME. They were aged from 29 to 50 years old ($M=38.9$). Everyone reported to have normal or corrected-to-normal vision, and not to be color blind. One person reported to have recurrent pain on their wrists, which information could help us to determine whether this condition affected their experience while using the TM technique to animate time.

Procedure

The experiment happened in three exploratory sessions, each one involving two to four participants (according to their availability) individually working in the same room to complete a set of tasks using visual and interaction tools of eSTIME. The sessions had a time limit of 3 hours and were accompanied by three experimenters, who would help participants with any questions they had regarding any aspect of eSTIME (e.g., conceptual, visual, interactive). During the whole experiment, the experimenter would listen to users' feedback and take notes on their behavior while using the system.

Each session started with a 15-minutes presentation about the experiment goals, the system purpose and overall mode of operation. We gave participants a moment to read and sign the Term and Conditions agreement (see Appendix G.1), and asked them to answer a socio-demographic questionnaire. During the learning phase, we asked participants to follow a semi-automatic tutorial embedded in the Control Unit, through which they could learn how to use the data selector (i.e. the tab-based menu and navigation bar) to visualize and modify indicators, and to associate an analytical dashboard. This phase took around 15 minutes and participants were assisted during the whole process to ensure the tools were correctly configured.

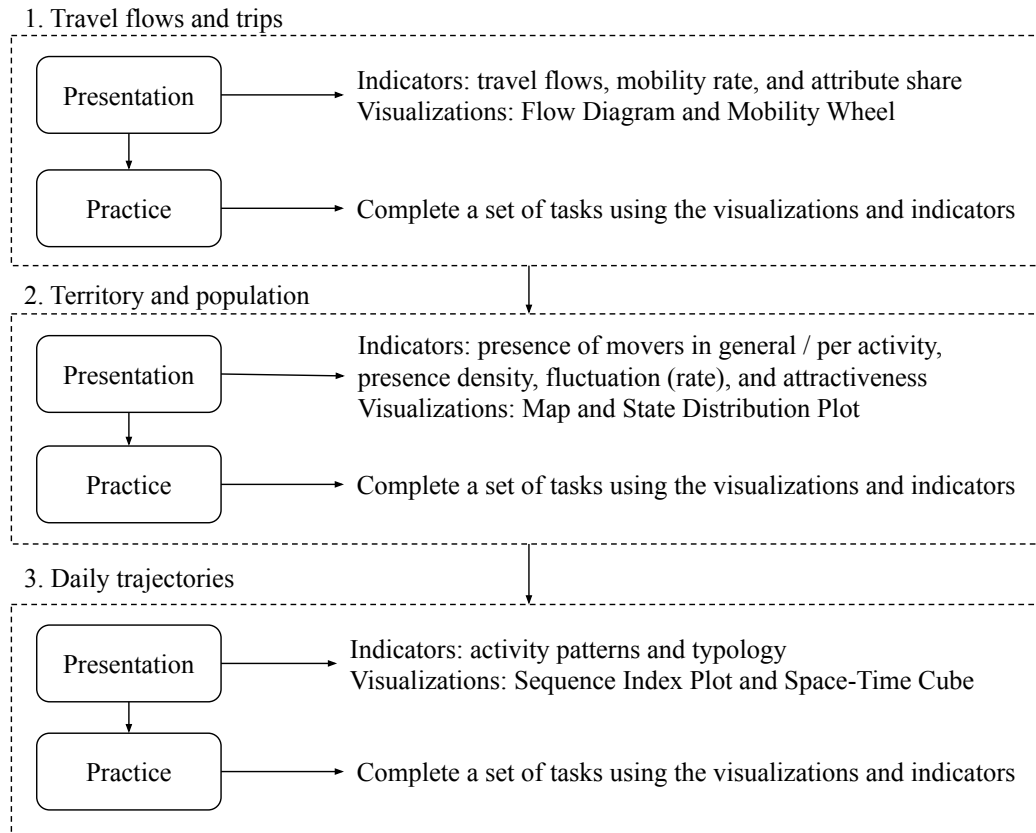


Figure 4.6.3: Protocol of the trial phase of Experiment IV.

Figure 4.6.3 presents the protocol followed during the trial phase, which took around 2 hours. In order to ease the introduction of participants to the visual and interaction tools, we split this phase into 3 moments corresponding to the three objects of interest within the data we represent through the available indicators and visualizations. Before starting the tasks, we made a short presentation regarding the indicators derived from the data and visualizations chosen to explore the corresponding object of interest. Afterwards, participants could take their time to explore the indicators and visualizations in order to complete the tasks. Despite temporal constraints, we allowed users to take their time to thoroughly explore the visual and interaction tools without pressure to complete every task.

The final 15 minutes of each session were devoted for the post-test questionnaire, which gathered the subjective usability and perceived workload through the SUS and Raw TLX questionnaires, respectively. Further, we asked them to rate on a 5-points Likert scale how much they agreed with each one of the following statements:

- I enjoyed using the tablet for interacting with the visualizations.
- I enjoyed using multiple displays for exploring the data.

Tasks

Table 4.6.1 presents the three sets of tasks we asked participants to complete. Each set focus on one of the following objects of interest: travel flows and trips, population and territory, and daily trajectories. These tasks were intended as a guide to what kind of analysis can be performed using our geovisualization environment. Therefore, participants were free to complete tasks using the data set (i.e. Grenoble, Lyon or Rennes) and territorial partition of their choice, and to explore alternative hypotheses regarding the data.

Apparatus

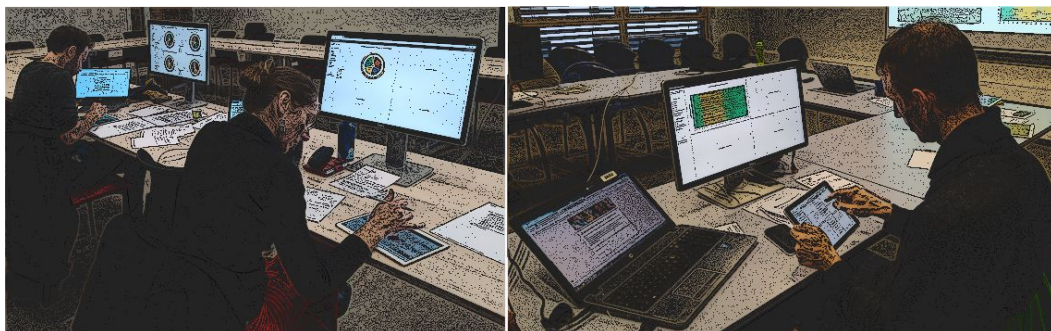


Figure 4.6.4: The apparatus and setup of the Experiment IV. Two or four people side-by-side would explore the visual and interactive tools to complete the proposed tasks.

Each participant was placed on a workstation containing one 24-inch monitor and a tablet device. The former held the analytical dashboard, while the latter served to run the Control Unit, which device could be a 10.5-inch Galaxy Tab S (1 device) or a 9.7-inch Galaxy Tab S3 (3 devices in total) (Figure 4.6.4). We provided a document containing the indicators and visualization descriptions, which they could use as support, and a paper sheet containing the tasks. They could write their answers directly on the paper sheet or type them on an interactive version of the questionnaire. Further, we provided a notebook, where they could take notes to support their analysis.

Set 1. Travel flows and trips (for the 3 most attractive spatial locations)	
1	$t \rightarrow S \rightarrow M$: How many people travel there over 24 hours.
2	$t \rightarrow (S \times A) \rightarrow M$: What are the purposes of their trips over 24 hours.
3	$t \rightarrow (S \times A) \rightarrow M$: What are the transportation modes used for traveling there over 24 hours.
4	$T \rightarrow S \rightarrow M$: Which are the time units when there are more/less people traveling there.
5	$t \rightarrow (S \times S) \rightarrow M$: How many trips are connected to these spatial locations over 24 hours. Where the outgoing/incoming flows go to/come from.
6	$T \rightarrow (S \times S) \rightarrow M$: How many trips are connected to these spatial locations during the time units with the highest mobility rate. Where the outgoing/incoming flows go to/come from.
Set 2. Population and territory dynamics	
7	$T \rightarrow S \rightarrow M$: How the spatial distribution of people varies along the day.
8	$T \rightarrow (S \times A) \rightarrow M$: How the spatial distribution of people varies along the day according to different activities.
Set 3. Daily trajectories	
9	$s \rightarrow (A \times T) \rightarrow M$: How the distribution of people per activity varies over time in the whole region.
10	$O \rightarrow (T \times A) \rightarrow M$: Describe the different groups of the typology according to individuals' activity patterns.
11	$O \rightarrow A \rightarrow M$: Which is the socio-demographic profile of individuals in different groups of the typology.
12	$O \rightarrow (A \times T) \rightarrow M$: How the distribution of people per activity varies over time for the different groups of the typology.
13	$O \rightarrow (S \times T) \rightarrow M$: How are shaped the spatio-temporal paths of individuals in the different groups of the typology.
14	$A \rightarrow (S \times T) \rightarrow M$: How are shaped the spatio-temporal paths for individuals according to different socio-demographic criteria (e.g., gender, occupation, age).

Table 4.6.1: Set of tasks used during the trial phase of the Experiment IV.

4.6.4 Results

Usability

The mean score of the SUS questionnaire was 69.6 points ($SD = 14.9$) – grade C in the CGS (see Table 4.2.1) – which corresponds to a satisfactory usability score. We observed that the additional indicators and visualizations we included to complete the analysis of human mobility did not affect the assessed usability of our prototype, which continues satisfactory.

Figure 4.6.5 presents the participants ratings of statements regarding whether they enjoyed using the tablet as interaction device and the combination of multiple displays for exploring the data. Mean ratings were 4 over 5 points, suggesting that the technological setup of eSTIME was appreciate.

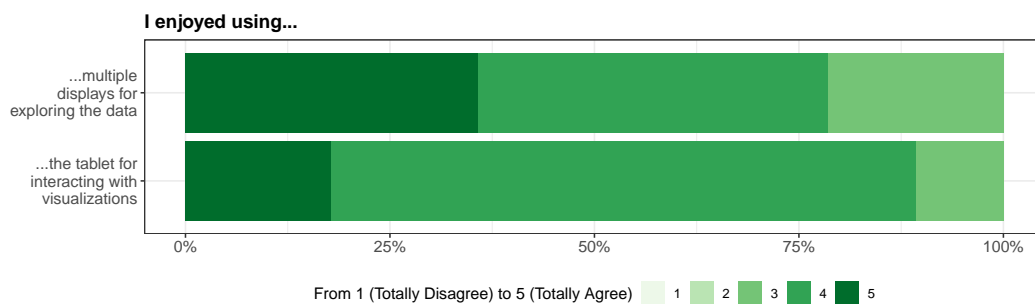


Figure 4.6.5: Participants ratings regarding the satisfaction statements in Experiment IV.

Workload

The mean score of overall workload (OW) was 37.6 points ($SD = 16.2$) over a maximum scoring of 100. Figure 4.6.6 presents the mean scores obtained for each sub-scale. Consistent to previous experiments, the mental demand was perceived as the main source of workload ($M = 52.9$, $SD = 9.51$). Mean scores of physical demand ($M = 20$, $SD = 12.9$) and frustration ($M = 22.9$, $SD = 9.51$) scales were the lowest among all factors.

Considering a 90% confidence level, we found correlations between mean scores of effort (EF) and own performance (OP) with participants' profile. We found a negative 58% correlation between EF and age ($p = .08$), which

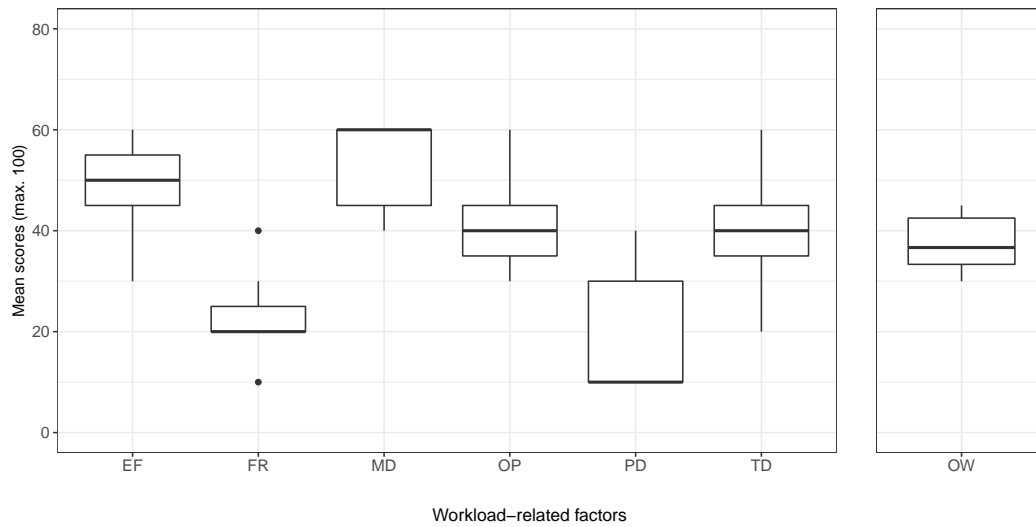


Figure 4.6.6: Mean scores of RTLX questionnaire per sub-scale and overall workload.

suggests that older participants would perceive the task more effortful than younger ones, and a 58% correlation between OP and their experience using multiple displays in their everyday routine ($p = .094$), suggesting that people with more experience on handling information distributed over multiple displays evaluate the quality of their performance as higher than the ones who would normally work with a single display.

Users Reaction

During this experiment, the information regarding how indicators were calculated and what they represent was provided on an external document, which users could access during the whole time. However, participants reported to prefer having this information embedded in the interface, which would facilitate the understanding and use of visualizations.

The state distribution plot was overall appreciated by the experts, since it allows to understand an entire temporal situation at a glance. Interpreting the sequences index plot was harder due to users lack of experience with this type of representation, and because the sequences were displayed without any particular arrangement, which hindered the extraction of information, such as existing sub-clusters of similar activities. One expert suggested to sort

the sequences according to a particular criterion (which was done after the experiment), or to display only the x (e.g., ten) more frequent sequences.

Although the mobility rate indicator can be calculated both by counting trips or movers traveling towards a particular location, the prototype included only the latter. This choice hindered the understanding of this indicator by people who have long experience studying mobility rate based on the counting of trips. One expert said that “linking trip purpose to people is unnatural” when talking about mobility. They also suggested to re-categorize the modes as particular, public and smooth transportation, and to represent them through opposing colors due to their importance during decision-making process within urban policies, where the difference among these categories of transportation are used to measure aspects such as population’s well-being. Currently car and public transportation are represented through different tons of blue, which could cause them to be interpreted as having similar impact on mobility.

The general definition of our indicators and the system of tasks allow to query them over different groups of our typology of activity patterns. However, the prototype does not support filtering travel flows neither presence indicators for different groups of individuals, which was noticed by our experts and suggested as an interesting feature to include. Further, experts evoked the necessity of a feature that enables the definition of different temporal granularity levels, since longer intervals than one hour are often more statistically significant for the analysis.

The satisfaction expressed about using multiple displays might reflect the usefulness of comparing several indicators side-by-side, according to the description of an expert on how they explored two indicators for different spatial locations. They visualized the mobility wheel for each location on the top windows of the dashboard and the flow diagram of each one on the bottom windows, being able to simultaneously compare the locations according to both indicators.

The head of studies within public agencies alerted us to the fact that tablets are not yet a common device on their working environment, making it difficult for them to integrate our tool into their working routine. Nevertheless, they showed great interest on having such a visual analysis tool that they can handle by themselves (without the intermediary of a cartographer technician for example) in order to explore the various indicators in all the locations in which they have to intervene on a daily basis. Further, they found the tool

overall interesting, easy to use and “ready to be used without problems and adopted in its present version”. One expert suggested to use eSTIME as a presentation tool, in which users would produce their analysis in “real time”, while presenting it to the public of interest.

4.6.5 Synthesis

Hypotheses Assessment

H1: *the experts will appreciate our visualization environment to explore daily mobility data.*

Our results showed the appreciation of experts regarding our visualization approach through the satisfactory SUS and RTLX scores, which show their perception of effectiveness and satisfaction while using the environment. Their observations and suggestions regarded some indicators and visualizations (i.e. statistical significance, using different data categories, opposing colors for variables with opposed meaning within urban planning studies), and the difficulty of introducing such a tool in their everyday work routine due to the use of multiple displays and a tablet. Nevertheless, they claimed to have appreciated using the tablet and multiple displays, which latter has proven useful for comparing indicators side-by-side, facilitating the analysis. Hence we **accept** this hypothesis.

After modifying our prototype to improve the intuitiveness of our interaction mechanisms and the visualizations, while extending them to include the remaining indicators that allow the analysis of daily mobility data through the exploration of three complementary objects of interest (i.e. travel flows and trips, territory and population, and daily trajectories), we conducted a final experiment to gather feedback from experts regarding the usefulness of our visual and interactive tools. We invited eight experts, researchers of human mobility, working on the academy or within urban planning to assess the current transportation solutions and overall mobility-related aspects, and propose foresighted strategies aiming to improve mobility of population within urban areas.

The SUS and RTLX scores showed that assessed usability is satisfactory, while the overall workload score is below average, indicating that a low amount

of work is required for using our prototype. The mean scores are similar to the ones obtained in the Experiment III (see Section 4.5.4), when the participants (geography students working on the subject during that semester) had about 6 hours of learning time, which allowed them to get comfortable with the visual and interaction tools. In this experiment, due to temporal constraints, participants had to learn quickly how to interact with the visualizations through an embedded tutorial in the Control Unit. A short presentation and a cheat-sheet material were provided to help them to understand the visualizations that they were supposed to use for completing the tasks, which were themselves more complex than the ones in the previous experiment since they were exploratory and involved more indicators (i.e. activity patterns) and data dimensions (i.e. activities and trip purposes). Therefore, we observe that with less training and more indicators/visualizations, users were capable to explore the data to complete the tasks, while judging the interface usable (one expert even called it a “therapeutic experience”) and perceiving low overall workload.

The participants gave us valuable feedback regarding the indicators and visual representations. There are still improvements to be made, particularly:

- to better communicate the description of indicators (e.g., how were they calculated, what feature of the phenomenon are they measuring, how many data records were used as input (for statistical significance verification), etc);
- to improve visualization reading (e.g., use histograms instead of proportional circles to avoid overlapping, and use a relevant criterion to sort sequences in the index plot); and
- to increase the power of analysis (e.g. through the interactive definition of different time granularity levels).

Some of these improvements were already applied to the prototype, such as the ordering of sequences. Particularly, the interactive definition of time granularity levels and automation of the analysis process (i.e. indicators recalculation) was the subject of a internship that took place after the experiment, which outcomes are the starting point to include the feature on eSTIME.

Despite the improvements necessary and small problems found during the experiment (i.e. the resolution of analytical dashboards is not compatible to smaller than 24-inch displays with a 1920×1080 resolution), the experts

enjoyed using our visualization approach, finding that it is accessible and easy to use, and that it could be already employed for analyzing daily mobility data.

4.7 Summary

In this chapter, we presented the methodological procedures we followed to evaluate the usefulness our visualization framework, eSTIME, and the usability of the visual and interaction tools. The main characteristic of a user-based evaluation is that it involves the users, preferentially the ones for whom the system was designed. Regardless of their profile or the experiment's goal, we are asking these people to take a moment of their time for using a tool in development, which could be buggy and incomplete, while following a strict protocol and giving their opinions about it.

The evaluation of a visualization system, specially one that represents multivariate data, requires the assessment of various aspects, such as verifying that maps and charts are comprehensible and able to efficiently transfer information, and that the interaction mechanisms allow users to freely browse within the visualization interface to extract the data information they need, and assessing the added value of multiple visualizations to investigate the domain-related questionings. While assessing map/chart reading and the usability of interaction mechanisms is achievable through simple tasks such as locate, identify, and compare, the evaluation of added value require more exploratory tasks. These are difficult to replicate in an experiment and take long to be completed due to their intrinsic complexity involving multiple data dimensions and granularity levels, and because one needs to become accustomed with the visual and interaction tools before actually exploring the data representations for completing the tasks.

The visual and interaction techniques embedded in our visualization framework are not novel per se, as we could observe in Section 2. However, to the extent of our knowledge, the novelty lies on combining them to allow a flexible exploration of urban mobility data via three complementary objects of interest through a multi-display system embedding customizable analytical dashboards, which can themselves hold multiple views simultaneously while supporting interaction through tactile and tangible input from a mobile device. This fusion of rather non-conventional interaction techniques with the

usage of multiple conventional displays could engender high cognitive load which, consequently, could affect user performance while exploring the data.

EXP	Workload	Usability	Accuracy
1	63.7	58.3	0.86
2	Not applicable	47.3 ⁱ	0.76 & 0.5 ⁱⁱ
3	33.3	69.9	0.81
4	37.6	69.6	Not applicable

ⁱ In average for all experimental conditions. No statistical significance in the difference of means.

ⁱⁱ Response accuracy was significantly lower when using the TM technique with a circular tilting movement than the remaining conditions, within which scores were about the same.

Table 4.7.1: Summary of user experiments outcomes.

In this context, we followed an incremental evaluation protocol that enabled us to refine our visual and interaction tools based on continuous user feedback. We performed a total of four evaluations with the participation of users that were non-experts on the domain of urban mobility, trainees learning the concepts of the domain, and experts actively working on the field. Table 4.7.1 summarizes the scores of overall workload, usability and response accuracy (when applicable) for every experiment, which allows to determine how each refinement step affected these variables. Overall, we notice that each evaluation allowed us to improve the interface intuitiveness which yielded positive effects on usability and workload, while response accuracy remained sufficient to suggest that our framework enable the understanding of the urban mobility phenomenon. We summarize the experiments goals and outcomes as follows:

- the *experiment I* (Section 4.3) evaluated the usability of a first prototype, and focused on understanding how users would respond to a multi-display approach and to the *TiltingMap* technique. This prototype enabled the exploration of urban mobility data through the following:
 - Objects of Interest: territory, travel flows and trips;
 - Indicators: travel flows, mobility rate, transportation modes share, presence density, fluctuation rate and attractiveness;
 - Views: flows diagram, mobility wheel, and map view.

The main outcomes were:

- There was a lack of intuitiveness in the interaction mechanism that established the relationship between control unit and dashboards;
 - Legends and details-on-demand are essential;
 - The circular movement is difficult to perform;
 - Users found that the approach has potential;
 - Users need longer learning time to master the visual and interaction tools;
 - Major improvements and further studies with experts are necessary; and
 - Despite the necessary improvements, the response accuracy is encouraging.
- the *experiment II* (Section 4.4) evaluated the usability and suitability of the *TiltingMap* technique for exploring indicators of presence dynamics over time compared to the traditional animation technique. The main outcomes were:
 - The circular movement is difficult to perform and negatively affects response accuracy;
 - Response accuracy is encouraging while using the TM technique with linear tilting movement;
 - The TM technique with linear movement is as effective and efficient as the traditional animation;
 - Users enjoyed controlling the TM technique with a linear tilting movement; and
 - Combining direct touch to the TM technique may improve interaction.
- the *experiment III* (Section 4.5) evaluated a refined version of the visual and interaction tools of the previous eSTIME prototype, covering the exploration of urban mobility data through the same indicators, objects of interest, and visual representations. However, supporting the *TiltingMap* through a linear tilting movement instead of a circular one. The main outcomes were:
 - Users could learn how to use the visual and interaction tools;
 - Users enjoyed using the tablet to interact with the analytical dashboards;

- The modifications reduced workload and increased usability comparing to the first experiment;
 - More interaction mechanisms are necessary between tablet and dashboards; and
 - Users evoked the need for a technique that allows to freezing space and time.
- the *experiment IV* (Section 4.6) evaluated the usability and suitability of a complete version of eSTIME to support the analysis of urban mobility data through the exploration of three complementary objects of interest over space, time and thematic attributes. This experiment involved experts actively working on the field. The main outcomes were:
 - Users could explore the data without much training, which reflects into a satisfactory usability and intuitiveness of the visual and interaction tools of eSTIME;
 - Usability and overall workload scores were similar to the previous experiment, which are both satisfactory;
 - Users provided valuable feedback regarding the indicators, specially the activity programs and mobility rate;
 - The multiple views layout was found useful to compare several indicators side-by-side;
 - Users told us that a tablet is not a common device on their working environment, and suggested using eSTIME as a communication tool.
 - Experts found the tool accessible, easy to use, and that it could be employed right away for analyzing urban mobility data.

From these experiments, we observed that a long time slot should be allocated for the learning phase and the trial phase would take around one hour minimum if the experiment involved simple tasks. Particularly, we allocated a slot of six hours for training a group of geography students (enthusiasts of human mobility) on how to use our visualization system for discovering and describing human mobility patterns. However, students are usually easy to recruit and they have more time to spare, while the same cannot be expected from expert users.

In our final experiment we provide a short learning time and allow the experts to freely explore the tool trying to solve a set of exploratory tasks that

would serve as a guide to what they could do within the system. The expert users were able to progressively learn how to use the visual and interaction tools, which consequently led some of them not being able to complete all tasks during the two hours allocated for the trial phase. Nonetheless, this could also be consequent from exploring their own hypotheses, since we did not force them to strictly follow our list of tasks. They found the interface easy to use and reported low overall workload. Therefore, we believe that performing periodic experiments with specific objectives for finding obvious usability issues and refining the system is a suitable solution for minimizing the time of experiments, while making them more attractive to volunteers and reducing the time necessary for learning to manipulate the visual and interaction tools.

The literature has exhaustively mentioned that the test users of a visualization tool should be the potential users from whom it was designed (Ellis and Dix, 2006, Knight, 2001, Shneiderman and Plaisant, 2006), since they understand the domain's needs and know better than anyone what functionalities they need from it. While we agree with this statement, a recurring problem with evaluations is the difficulty to find a group of expert users to take part in the many trials necessary for evaluating a visualization system, which lead to conveniently using students. Regardless the negative tent of replacing expert users by students, they can be valuable on detecting usability issues, since these can be identified through simple identify, locate and compare tasks, for which one does not need to be an expert on the application domain. The feedback gathered from two groups of non-experts on the subject and a group of trainees, which were students on geography being trained on human mobility during that semester, was extremely valuable for refining our tool and having an interface with satisfactory usability for presenting to the expert users. Thus, we could have a feedback from experts mainly focused on the data and exploratory process, instead of issues regarding the interface usability.

The next and final chapter concludes the work carried out during this thesis, while discussing the limitations of our framework and exploring the perspectives of future research resulting from this work.

Conclusion

Numerous experts in urban policies – not necessarily transport specialists – need to manipulate more or less standardized urban mobility data to extract synthetic and easily exploitable knowledge that serve as support for the decision-making process on public policies such as transportation offers, accessibility, public health, well-being, and air quality control. In this thesis, we focused on assisting these professionals through a visualization framework that enables the answering of three great questions underlying the urban mobility phenomenon and that are of great concern within the fields of geography and urban planning. These questionings pursue the understanding of:

- how people travel within an urban area on a daily basis, which are the resulting exchange processes and how they shape the urban structure. In this context, the objects of interest are *travel flows and trips*, from which we derive indicators that describe their amounts, modalities, direction, and variation according to different socioeconomic aspects of individuals and land types;
- how the different spatial locations within an urban area are used according to the socioeconomic characteristics of people that visits them and the types of activities they carry out there. Here, the object of interest is the *territory*, which is explored through indicators that describe the temporal variation of presence in the spatial locations that constitute the territory. This analysis reveals the urban pulse of different spatial locations (Miranda et al., 2016), which enables a better understanding of their daily rhythms (Le Roux et al., 2017); and
- how people order their activities and trips according to the spatial context of the studied territory, which helps to explain their need of traveling. In this case, the object of interest is the *daily trajectory* of individuals, which are defined as the travel-activity schedules resulting from

the daily mobility of individuals, i.e. the sequence of trips and activities one perform within the period of a day.

The answering to these questionings can be achieved through the visual exploration of a dataset describing individual trips in space (i.e. a urban area) and time (i.e. 24 hours), and characterized by reasons to travel and used transportation modes. The individuals are themselves characterized through socio-demographic aspects, such as age, occupation, and place of residence. These multivariate aspect of the data implies on manifold indicators defined over space, time, objects and thematic attributes, which analysis can become rapidly complex when considering multiple levels of aggregation and granularity. This way, information visualization is a suitable approach to support the analysis of urban mobility data, since analysts do not have to learn sophisticated methods to interpret the data visualizations that come to reinforce their cognition, enabling the discovery of unstructured insights within the data.

Although there are a great amount of work being done in information visualization aiming the analysis of urban mobility data, we have not found visualization approaches that allow the understanding of urban mobility phenomena through the analysis of complementary objects of interest, specially the ones that support the answering to the above questionings. Particularly, we identified the following issues from our literature review:

- the majority of surveyed studies focus on exploring specific issues of urban mobility analysis, particularly regarding urban traffic flows and monitoring, people dynamics in an urban environment, road traffic accidents (Sobral et al., 2019), and more recently, the usage of bike-sharing systems, which not necessarily addresses the reasons that drive human mobility;
- the analysis is often supported either at the population or individual level, rarely at both;
- thematic attributes are rarely represented, which probably results from the type of data they explore (e.g., public transportation and bike-sharing data);
- only two surveyed VAS support urban mobility analysis via our three objects of interest, but the visual representation is completely based on 3D techniques which interaction remains restrict to 2D operations, causing issues such as occlusion and loss of information;

-
- the majority of surveyed studies, including the ones supporting the complementary analysis through our three objects of interest, did not evaluate the proposed VAS with participation of users, which makes it difficult to assess whether these proposals are suitable for our potential users; and
 - the visualization interface, although built on the basis of multiple coordinated views, present views in a predetermined spatial arrangement, which prevent the user of modifying that arrangement or replacing views for data representations that are more suitable to the ongoing analysis. For instance, instead of exploring a particular indicator using a single view which variation over space, time and thematic attributes is presented one at the time according to the selection of a spatial location, time unit or attribute, one could prefer to compare the indicator over those different attributes side-by-side by displaying a new instance of the view built with different data attributes.

In this context, designing a visualization framework that supports the efficient exploration of urban mobility data requires to address issues regarding visualization, interaction, and user-based evaluations, described as follows:

- from a visualization perspective, we sought to identify, among the great range of well-known visualization techniques largely used to represent spatio-temporal data, the ones that were appropriate to visualize the variation of indicators describing the territory, travel flows and trips, and daily trajectories over multiple spatio-temporal granularity levels and thematic attributes. Furthermore, when the existing techniques were not suitable to our requirements, we sought to improve them or propose novel ones;
- from the interaction perspective, we sought to establish the relationship of indicators with the multiple granularity levels of space and time, and the various thematic attributes through interaction mechanisms. We were particularly interested on:
 - improving the way users explored data over time, since the traditional animation techniques have shown shortcomings due to being strongly dependent on users' memory;
 - supporting a comfortable and efficient interaction with a large and customizable visualization space, which would assist users on composing their visualization display according to the ongoing analysis; and

- supporting the data synchronization within multiple visualizations and analytical displays.
- from the perspective of user-based evaluations, we sought to identify suitable experimental protocol(s), measures, metrics and user profiles that could help us to evaluate the usability and suitability of our visualization framework.

5.1 Summary of Contributions

In order to overcome the aforementioned shortcomings, our main contribution consists of a visualization framework, eSTIME, which incorporate the process of transforming and deriving indicators from the input data to describe the territory, travel flows and trips, and daily trajectories. An interactive visualization interface supports the exploration of those indicators through appropriate visual and interaction tools, enabling the exploration of indicators over multiple spatio-temporal granularity levels and thematic attributes. eSTIME supports the integration of different datasets to allow comparison of daily urban mobility patterns within different urban areas. On a more particular level, it enables users to:

- describe daily mobility patterns through complementary analyses of travel flows and trips, territory, and daily trajectories, which indicators are defined and explored over multiple spatio-temporal granularity levels, and thematic attributes;
- explore and compare indicators at the aggregate **and** individual levels through suitable visual and interaction tools within a single interface to leverage their complementary aspect;
- explore the temporal variation of indicators to reveal the dynamics resulting from the urban mobility phenomenon; and
- compose the visualization display in meaningful ways according to the ongoing analysis. Although the complementary aspect of the indicators is essential for understanding the human mobility phenomenon as a whole, each aforementioned question could focus on indicators derived from only one object of interest, which could be also interesting for the analyst. Assuming users may not need to deal with every indicator and

their spatio-temporal combinations simultaneously, we allow them to define the spatial arrangement of visualizations across multiple analytical dashboards and to modify them according to different indicators, spatial locations, time intervals and thematic attributes as it better suits their analysis.

Our visualization framework comprises contributions spread over two axes:

- *interaction*: we proposed a movement-based interface that enable the exploration of data over time and uses tactile input to handle the visual representations within our visualization interface; and
- *visualization*: we proposed a multi-display visualization embedding customizable analytical dashboards to enable the analysis of urban mobility data via the exploration of three objects of interest (travel flows and trips, territory, and daily trajectories), and according to the spatio-temporal granularity levels and thematic attributes that are suitable to the ongoing analysis.

Firstly, traditional animation techniques rely strongly on humans' memory, which presents some well-known issues for exploring data over time. Fish et al. (2011) draw attention to the blindness caused by subtle changes between time slices combined with the speed of animations, which reduces the effectiveness of animated maps, leading map readers to falsely believe they have correctly perceived more displays than they actually have. This misinterpretation of information would, in our context, mislead the production of knowledge that is further used to assist decision-making in important areas of public policies. Considering the benefits of physical interaction combined with humans' proprioceptive sense (Arvola and Holm, 2014, Besançon et al., 2017, Maciel et al., 2010) we proposed ***TiltingMap***, a movement-based interaction technique designed to offer more control of time animation and to improve map reading by using the position and orientation of the user's hands and wrists as reference recall for the observed changes between time slices. It implements the lenticular printing metaphor, allowing the user to view different time slices according to the tilting angles of a tablet, which are mapped to the time units displayed on a timeline.

Secondly, we designed and implemented ***eSTIME***, a multi-display visualization interface that embeds customizable analytical displays, which the

user can personalize in meaningful ways according to the ongoing analysis.

We provide users with a set of visualization techniques considered appropriate for representing each indicator. Most of them are not novel per se, except by the *mobility wheel*, which displays the temporal variation of mobility rate and attribute share simultaneously, allowing this information to be absorbed by the user at a glance. Our contribution lies on the design of a customizable interface that allow users to build the visualizations according to different indicators, spatio-temporal resolutions and thematic attributes that support the ongoing analysis, and to disperse the visual representations over multiple synchronized analytical displays in meaningful ways to build a visualization space that is suitable to their analysis. Furthermore, we leverage tactile input from a mobile device (i.e. a tablet) to interact with visualizations (i.e. open, close, modify indicators through data selection) in each analytical display. We also use the tablet screen to visualize indicators of presence through the map view, and daily trajectories on the space-time cube. Thus, eSTIME leverage a large visualization space that can be progressively increased via the addition of an analytical display, allowing the simultaneous exploration and comparison of multifaceted data through various indicators and over multiple spatio-temporal granularity levels and thematic attributes. The combination of customizable analytical dashboards and the *TiltingMap* technique offer the possibility of exploring data over time through juxtaposing and animation techniques, respectively. The former allows yet the comparison of indicators over different spatial locations and thematic attributes.

The usability and suitability of both proposals were assessed through user-based evaluations and many demonstrations involving experts on the domain. The results showed that our visualization system is suitable to explore the data, answering the questionings that guided this research, while being satisfactory with respect to overall usability and requiring a low amount of work from users (trainees and experts on urban mobility). Our visualization framework was well received by the expert users, who were able to quickly master the visual and interaction tools, and demonstrated interest on using the system to explore their own datasets, in particular other HTS data from different metropolitan regions of France for the purpose of comparison.

5.2 Future Research Perspectives

Hereafter, we delineate the research possibilities steaming from the work performed during this thesis.

Using provenance information to improve the analysis workflow

The design of eSTIME follows a flexible approach enabling the users to generate the analysis workflow that better suits the task in hand by choosing the indicators that describe the objects of interest they want to explore and the spatio-temporal granularity levels and thematic attributes suitable to their analysis. Nevertheless, user experience can be improved through the understanding of how analysts use a visualization interface such as eSTIME to solve different types of tasks, i.e. which selections and order of usage of indicators, spatio-temporal granularity levels, and thematic attributes, and how visualizations are dispersed over the multiple displays.

The field of *Analytical Provenance* focus on the understanding of users' reasoning process through the study of their interactions with a visualization, which addresses issues of perception, capture, encoding, recovering and reusing (North et al., 2011), through research questions such as follows:

- Perception: how the visual presentation of information affects the user's reasoning process?
- Capture: what types of user interactions should be captured, and how much semantic information should be included based on a user's task?
- Encoding: how should the system store the recorded user interactions?
- Recovering: how can a user's reasoning process be recovered from captured interactions, and could it be done automatically?
- Reusing: how can a visual analytics system apply what it had learned about a user's reasoning process to assist the user performing future analyses, and can the learned reasoning be applied to other tasks and systems?

In our context, eSTIME can be used in diverse ways to solve the same task, for example, “how does presence fluctuates over the day in the most attractive spatial locations?”, for which one would likely answer via the exploration of indicators describing the attractiveness and presence fluctuation at different spatial locations within the territory. However, the manner these indicators will be visualized and explored might change according to the usage one does of the system. Let us illustrate the solution of this task with three different possible usages:

1. The user displays on the *control unit interface* a map that represents the attractiveness index over 24 hours of every spatial location within the territory and they identify which are the most attractive ones. Subsequently, they would *replace* this indicator with presence fluctuation and use *animation* to identify its variation over the day.
2. The analyst chooses to use *only one analytical dashboard*, where they display a map representing the attractiveness index of every spatial location within the territory, and displays other three maps representing the indicator of presence fluctuation, each one frozen at a different time unit, exploring the temporal variation of the indicator through *time juxtaposing*.
3. The analyst displays a map representing the attractiveness indicator on the *control unit interface* and, subsequently, display on the analytical dashboard a map representing the presence fluctuation indicator and explore it through animation, or display four maps representing the presence fluctuation of different spatial locations and freeze them at four different time units to compare side-by-side.

Particularly, our system collects a set of operations considered relevant to understand these usage patterns, such as when and where a visualization was opened, closed, and modified (e.g., spatial granularity, time unit, spatio-temporal freezing). Identifying the most common usages of a system according to different types of tasks could be used to introduce the system to new users, such as by suggesting some well-known workflows of analysis, i.e. opening up visualizations at a certain order and dispersion to solve the task in hand. Furthermore, one should validate these usage patterns through a user-based evaluations involving experts on the domain, such as suggesting different analysis workflows according to a set of tasks and asking them whether that workflow responds to their needs and how it could be improved.

Data visualization and interaction in the space-time cube

The space-time cube is an important element of our visualization system, since it enables the visual exploration and understanding of the individuals' spatio-temporal ordering of activities and trips. According to Kraak (2003), alternative graphics should appear next to the cube and be linked together to stimulate thinking new insights and explanations. Particularly within our approach, the state distribution and index sequences plot serve to complement the information displayed on the space-time cube. Nevertheless, a limitation of our design lies on the interactive aspects that enable the user to effectively manipulate the cube in space to find the best possible view and query the cube's content. Furthermore, we only provide simple linking operations between the cube and index sequences plots, highlighting the corresponding sequence on the plot upon a selection on the cube's content.

In this regard, Kraak (2003) evokes a series of research questions, which certain remain open to this date: (1) how many multiple linked views can the user handle? (2) can the user understand the cube when multiple space-time-paths are displayed? (3) how should the interface look like? These questions can only be answered through user-based evaluations, which unfortunately are still scarce comparing to the amount of work that have been performed on the domain. Furthermore, as evoked repeatedly throughout this work, evaluations with the participation of users are difficult for several well-known reasons, which hinders the process of understanding which design choices are more suitable to help users explore data via multiple views and, more specifically, to leverage of often 2D visualizations linked to 3D representations.

As for the second question, the literature has shown that only a certain amount of data can be explored on the STC without causing occlusion. Likewise every other 3D representation, the STC suffers from well-known limitations in terms of perception and interaction when used in conventional desktop setups (Ware, 2019). In this spirit, researchers have lately focused their attention on mitigating the negative effects of using 2D operations to interact with 3D environments by using tangible interaction, which enables to map user actions in physical space into the virtual space of data in a visualization. These proposals are often combined with virtual reality as an attempt to improve perception by immersing the user in the virtual space of the visualization (Filho et al., 2020, Cordeil et al., 2017).

Another emerging field of research addresses the provision of spatial interaction through mobile devices (Fröhlich et al., 2007), which can serve as bridges between the real and virtual information space (Grandi et al., 2018). Our visualization framework leverages tangible interaction through the orientation of a mobile device. In this context, the interaction mechanism could be extended to map movements of forward/back, up/down, and left/right into the movement of the virtual camera enabling the user to find suitable views in a more natural fashion (Besançon et al., 2017, Pahud et al., 2018).

Whilst using spatial interaction may improve the relationship between user and 3D visualization, it requires the use of non-conventional interaction devices (e.g., mobile device, virtual reality headset) that are not part of the experts users' working routine, as evoked during our user-based evaluations. Therefore, "how to design comfortable interaction mechanisms for extended periods of work while leveraging spatial interaction and, eventually, virtual reality?" and "are resting mechanisms such as clutching and freezing (Kister et al., 2017) enough to support interaction during long periods?"

A second research aspect surrounding the STC refers to the visual encoding, which could be explored and extended to represent more complementary thematic variables. For instance, our implementation of the STC focus on representing activities. We put in place solutions that suits the data we were working with, such as using seven geographical coordinates within each spatial feature to represent the seven categories of activities that could be possibly performed in each spatial location. However, this design decision prevented us from appropriately representing transportation modes, since we cannot expect that everyone traveling to a particular spatial location for performing a specific activity would do so using the same transportation modes, which generates many segments between geographical positions that may overlay each other (i.e. multiple trips between the same O/D pair), hiding the color code of one or more transportation modes and causing, consequently, loss of information. Thus, "how to visually encode multiple variables without losing information neither overcharging the view?"

When representing daily trajectories, one could also be interested on exploring the overall spatio-temporal pattern, which could be shown through the visualization of kernel density estimation (Demšar and Virrantaus, 2010), or by aggregating trips between O/D pairs (Yu et al., 2015). These techniques eliminate the individual aspect of trajectories, but help to improve the exploration of the data since it reduces the volume of information been visualized. However, both visualization techniques evoke an issue regarding the represen-

tation of thematic attributes. Using kernel density estimation, the algorithm should be executed for every category of activity, which rise questions such as “how to display every pattern without increasing visual clutter?” and “is it useful to explore one pattern at the time?”. The aggregation of trips rises the same question we evoked above, “how to represent different variables, such as transportation modes and activities simultaneously?”.

Evaluating the visualization suitability with user participation

As we mentioned earlier, it might be almost impossible to completely evaluate a visualization interface (Ellis and Dix, 2006). Further to the difficulty of accessing expert users and replicating exploratory tasks to evaluate the suitability of the visualization to solve domain-related tasks, we encounter an extra challenge regarding the evaluation of the usability of our layout design (multiple synchronized displays) and non-conventional interaction mechanisms, as well as their suitability to assist the exploration of urban mobility data. Hence, we were confronted with evaluating how several variables could impact the usability of eSTIME: multiple indicators, visualizations, displays, and non-conventional interaction mechanisms.

This multiplicity of variables prevented us of following conventional evaluation protocols, which includes formal experiments comparing the product in hand with traditional interfaces and/or techniques. This format of experiment was only applied to evaluate the usability of the *TiltingMap* technique compared to traditional animation. Therefore, we adopted an incremental evaluation protocol following a quasi-experiment format, which outcomes have showed us that eSTIME can ultimately assist the analysis of urban mobility data and that users are able to use the interface after a short learning period, which is possible thanks to applying the outcomes of previous experiments focused on improving usability. However, we could notice that solving domain-related tasks with eSTIME takes a long exploration time, particularly when referring to exploratory tasks, and users repeatedly reported high mental demand while using the interface. We could hypothesize that these results are a consequence of the inherent complexity of the data, or from using visual and interaction tools users are not familiar with, or perhaps both.

These results show that we could validate the suitability of our approach to assist analysts on visually querying the data to answer their research questions. Nevertheless, our experiments could not show whether and how our design

decisions are better or worse than the traditional analytical dashboards. A direct comparison to an existing visualization interface would not be possible, since there is no system that provides the analysis of urban mobility data at the same extent as our framework does. Hence, the question that remains is “how to evaluate the effects of a multiple display interface combined with non-conventional interaction on usability and user experience compared to traditional visualization interfaces?” .

As we could observe through our literature review, there are little work on visualizing urban mobility data through non-conventional visual and interaction techniques, which makes the single display analytical dashboards and mouse/keyboard interaction the known way of expert users to visually explore this kind of information. Therefore, we believe that a solution could be to conduct a formal experiment comparing eSTIME with a “conventionalized” version of itself, which would display our six visualizations techniques side-by-side and completely coordinated them through brushing and linking techniques, while interaction would be provided through mouse and keyboard. In this scenario, the user would not have access to the time juxtaposing technique to compare indicators side-by-side, but they would rather use their memory to make comparisons with previously viewed information. This way, we would be able to determine the long exploration time and high mental demand origin based on the difference of these measures using a traditional analytical dashboard and eSTIME. Furthermore, this proposal could help to answer questions such as the following:

- Is eSTIME better than a traditional analytical dashboard in terms of usability (i.e. efficiency, effectiveness and satisfaction)?
- Are there effects of the absence and/or presence of time juxtaposing for the analysis and user experience?
- How using one or multiple displays affects the way users explore the data? Which are the effects on usability and user experience?

Collaborative visual analysis

Collaborative visualization involves two or more people using visualization tools to collectively frame and address a task (Brewer et al., 2000). It has become an important topic of research in the recent years due to analysts being

confronted with problems that are becoming increasingly large and complex, uncertain, ill-defined and broadly scoped, which makes it no longer feasible for a single analyst to tackle the immense datasets describing realistic problems that require broad expertise, diverse perspectives and a number of dedicated people to solve (Isenberg et al., 2011).

Collaboration can be achieved through the sharing of a physical or virtual space. Langner et al. (2018) have shown how people collaborate when working together on wall-sized visualization, which interaction was supported through mobile devices. This setup requires people to be located in the same physical space and to interact within the same visualization space. Another approach addresses the collaboration between users in different places working on the same problem at the same time (Hardisty, 2009). We could have two people working together in the same workstation, likewise the pair programming development technique, in which one person drives the interaction with the visualization, while the other, the observer, follows and provide insights on the data exploration.

During our experiments, one expert user suggested using eSTIME for communicating information by visualizing the data on a large high-resolution display or projection of one analytical dashboard and using the tablet for long-distance interaction. This setup would be useful since they constantly need to present the results of their analysis to the people responsible for decision-making within urban policies, allowing them to develop and even explore new hypotheses together with other team members. Using a secondary handheld device for assisting the presentation and “real time” exploration of a dataset on large screens have been proposed earlier on the literature (see Chegini et al. (2019) for an example). This setup could also support a form of collaborative visualization by involving two or more people in the discussion regarding the information being visualized.

Regarding the exploration of urban mobility data via eSTIME, collaboration could provide an alternative solution for combining 2D and 3D representations. For instance, the STC could be developed separately and explored through virtual reality techniques, which according to Filho et al. (2020), improves the user experience, while the remaining of indicators could be explored through 2D visualizations, such as within eSTIME. There are different possibilities on how the collaboration could happen in this scenario:

- both systems could be completely independent from each other, which would force users to inform each other about what they observe in each interface. Then, together they could formulate hypothesis and continue the exploration; or
- the systems could be synchronized, in a way that information (e.g., screenshots, annotations, messages) could be sent to one another allowing to integrate that new information in the ongoing analysis.

These forms of collaboration could also be integrated into eSTIME without virtual reality, but instead using two independent instances of the interface or by including communication protocols into a collaborative visualization session that enable people located in different spatial locations to explore together the same dataset.

Using eSTIME on different domains and/or datasets

The visual and interaction tools embedded into eSTIME are generic enough to enable the visual exploration of information other than mobility, or the analysis of mobility data described through alternative thematic attributes (i.e. other than activities and transportation modes). The temporal and spatial dimensions could be discretized into time periods (e.g., hours, weeks, months, years) and spatial locations that better suit the data, which requires a rather easy adaptation of the visual representations. Hereafter, we describe two examples of alternative application domains that could benefit from the visualizations embedded into eSTIME to answer domain-related questions. In both examples, we consider that the temporal dimension could be discretized into months or years, and the spatial dimension could cover the whole world or a single country, depending on the granularity level of the ongoing analysis. We describe the data and embedding process into eSTIME as follows:

- *life trajectories data* that describe the sequence of events over the lifetime of individuals. In this scenario, the thematic attributes would describe life events (e.g., new job, marriage) that may trigger a relocation to another city, state or country. We could represent the individual trajectories using the state distribution plot, index sequences plot and the space-time cube subsequently to similarity analyses (Robette, 2011), such as we performed to classify the activity patterns. The flow diagram

could serve to represent the relationship between spatial locations according to different life events, which reveal the migratory patterns of people throughout life. Similarly, the map view can show where people are living during different periods of time and why they moved there. Finally, the outermost ring of the mobility wheel could represent the number of people relocating to a certain spatial location, while the innermost ring could display the distribution of life events that triggered the relocation; and

- *scientific publications data* that describe where and when a paper was published, whom it belongs, and which topic it addresses. In this scenario, the thematic attributes could describe categories of research topics. We could adapt eSTIME to represent relationships between publications using the flow diagram such as the aggregation of publications between pairs of authors or topics. For one author/location or a set of authors/locations, the mobility wheel could display on the outermost ring the number of publications per time period, while the innermost ring could display the distribution of covered topics. Similarly, the map view could display the spatial distribution of publications per topic/author at different time periods. The state distribution plot could display the temporal variation of the number of publications per topic, which could be explored per spatial location and/or author. Finally, the index sequences plot and the space-time cube could serve to explore the individual “publication path” of different authors, allowing to analyze the frequency of publications over space and time according to different topics, as well as to identify their periods of inactivity.

As we can observe, it is possible to visualize different datasets through eSTIME, assisting the exploration of different data and therefore the understanding of phenomena other than urban mobility. Nevertheless, the suitability of this approach to solve domain-related tasks should be validated through user-based evaluations involving expert users of the referred domains. Regardless of whether eSTIME is adapted or not to assist the analysis of data from other field of researches, further investigation remains necessary to verify the suitability of our design decisions and whether they are better or worse than the traditional single display analytical dashboards.

5.3 Final Considerations

This thesis was developed within an interdisciplinary research group that focus on proposing models, methods and tools to improve acquisition, modeling, querying, reasoning and visualization of spatio-temporal data, which topics are at the confluence of many disciplines, particularly Computer Science and Geography (i.e. Geographic Information Science or *Geomatics*). This cooperation between computer scientists and geographers prevail since 2007, which long-term teamwork allowed to improve the communication between researchers from different backgrounds, enabling the development of efficient solutions to assist spatial analysis, natural hazard prevention, and digital humanities.

Particularly, the work accomplished during this thesis is a product of the cooperation of researchers within the fields of Computer Science, *Geomatics*, and Geography, which latter corresponds to a researcher with a deep knowledge on human mobility and, therefore, able to understand the needs of social scientists towards the subject and to accompany the development of our visualization framework from a thematic point of view. This cooperation among disciplines supported an extensive work in order to understand and exploit the datasets describing the urban mobility phenomenon. This process of comprehension of a real dataset improved not only the derivation of proper indicators and the definition of suitable visual representations, but contributed for a greater comprehension of the application domain. Further, we could develop a procedure of data processing, indicators derivation and visualization generic enough to fast and easily integrate new datasets from similar data sources.

Bibliography

- [[Abel, 2018](#)] Abel, G. J. (2018). Estimates of global bilateral migration flows by gender between 1960 and 2015. *International Migration Review*, 52(3):809–852. [120](#), [243](#)
- [[Adams, 1995](#)] Adams, P. C. (1995). A reconsideration of personal boundaries in space-time. *Annals of the Association of American Geographers*, 85(2):267–285. [25](#), [243](#)
- [[André-Poyaud et al., 2008](#)] André-Poyaud, I. I., Chardonnel, S., Charleux, L. L., and Tabaka, K. (2008). La mobilité au cœur des emplois du temps des citadins. In Yves Chalas, F. P., editor, *La mobilité qui fait la ville*, Débats, pages 67–95. CERTU. [102](#), [243](#)
- [[Andrews et al., 2011](#)] Andrews, C., Endert, A., Yost, B., and North, C. (2011). Information visualization on large, high-resolution displays: Issues, challenges, and opportunities. *Information Visualization*, 10(4):341–355. [71](#), [72](#), [243](#)
- [[Andrews and North, 2012](#)] Andrews, C. and North, C. (2012). Analyst’s Workspace: An embodied sensemaking environment for large, high-resolution displays. In *2012 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pages 123–131. IEEE. [71](#), [243](#)
- [[Andrews, 2006](#)] Andrews, K. (2006). Evaluating information visualisations. In *Proceedings of the 2006 AVI workshop on BEyond time and errors: novel evaluation methods for information visualization*, pages 1–5. [81](#), [82](#), [83](#), [243](#)
- [[Andrienko and Andrienko, 2007](#)] Andrienko, G. and Andrienko, N. (2007). Coordinated multiple views: a critical view. In *Coordinated and Multiple Views in Exploratory Visualization, 2007. CMV’07. Fifth International Conference on*, pages 72–74. IEEE. [35](#), [36](#), [243](#)
- [[Andrienko and Andrienko, 2010](#)] Andrienko, G. and Andrienko, N. (2010). A general framework for using aggregation in visual exploration of movement data. *The Cartographic Journal*, 47(1):22–40. [87](#), [243](#)
- [[Andrienko et al., 2011](#)] Andrienko, G., Andrienko, N., Bak, P., Keim, D., Kisilevich, S., and Wroble, S. (2011). A conceptual framework and taxonomy of

- techniques for analyzing movement. *Journal of Visual Languages & Computing*, 22(3):213 – 232. Special Issue on Visual Analytics and Visual Semantics. 88, 150, 243
- [[Andrienko et al., 2016a](#)] Andrienko, G., Andrienko, N., Fuchs, G., and Wood, J. (2016a). Revealing patterns and trends of mass mobility through spatial and temporal abstraction of origin-destination movement data. *IEEE transactions on visualization and computer graphics*, 23(9):2120–2136. 41, 42, 66, 244
- [[Andrienko et al., 2003](#)] Andrienko, N., Andrienko, G., and Gatalsky, P. (2003). Exploratory spatio-temporal visualization: an analytical review. *Journal of Visual Languages & Computing*, 14(6):503–541. 111, 244
- [[Andrienko et al., 2016b](#)] Andrienko, N., Andrienko, G., and Voss, H. (2016b). *Exploratory Analysis of Spatial and Temporal Data: A Systematic Approach*. Springer Publishing Company, Incorporated. 26, 244
- [[Andrienko et al., 2008](#)] Andrienko, N. V., Andrienko, G. L., Pelekis, N., and Spaccapietra, S. (2008). Basic concepts of movement data. 110, 244
- [[Anwar et al., 2014](#)] Anwar, A., Nagel, T., and Ratti, C. (2014). Traffic origins: A simple visualization technique to support traffic incident analysis. In *2014 IEEE Pacific Visualization Symposium*, pages 316–319. IEEE. 4, 26, 51, 66, 244
- [[Arvola and Holm, 2014](#)] Arvola, M. and Holm, A. (2014). Device-orientation is more engaging than drag (at least in mobile computing). In *Proceedings of the 8th Nordic Conference on Human-Computer Interaction: Fun, Fast, Foundational*, pages 939–942. ACM. 32, 130, 182, 231, 244
- [[Bach et al., 2017](#)] Bach, B., Dragicevic, P., Archambault, D., Hurter, C., and Carpendale, S. (2017). A descriptive framework for temporal data visualizations based on generalized space-time cubes. In *Computer Graphics Forum*, volume 36, pages 36–61. Wiley Online Library. 24, 30, 56, 244
- [[Baglioni et al., 2008](#)] Baglioni, M., Macedo, J., Renso, C., and Wachowicz, M. (2008). An ontology-based approach for the semantic modelling and reasoning on trajectories. In *Advances in Conceptual Modeling – Challenges and Opportunities*, pages 344–353. 88, 244
- [[Bahoken, 2016a](#)] Bahoken, F. (2016a). La cartographie d’une sélection globale de flux, entre ‘significativité’et ‘densité’. *Netcom. Réseaux, communication et territoires*, (30-3/4):315–340. 100, 244

- [Bahoken, 2016b] Bahoken, F. (2016b). *Mapping flow matrices, a contribution*. Theses, Université Paris Diderot (Paris 7). 30, 41, 120, 245
- [Baldonado et al., 2000] Baldonado, M. Q. W., Woodruff, A., and Kuchinsky, A. (2000). Guidelines for using multiple views in information visualization. In *Proceedings of the working conference on Advanced visual interfaces*, pages 110–119. ACM. 36, 114, 245
- [Bertin et al., 1967] Bertin, J. et al. (1967). *Sémiologie graphique*. Paris, Mouton/Gauthier-Villars. 26, 245
- [Besançon et al., 2017] Besançon, L., Issartel, P., Ammi, M., and Isenberg, T. (2017). Hybrid tactile/tangible interaction for 3d data exploration. *IEEE transactions on visualization and computer graphics*, 23(1):881–890. 32, 130, 231, 236, 245
- [Bezerianos and Isenberg, 2012] Bezerianos, A. and Isenberg, P. (2012). Perception of visual variables on tiled wall-sized displays for information visualization applications. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2516–2525. 72, 245
- [Blondel et al., 2015] Blondel, V. D., Decuyper, A., and Krings, G. (2015). A survey of results on mobile phone datasets analysis. *EPJ data science*, 4(1):10. 39, 245
- [Borsci et al., 2015] Borsci, S., Federici, S., Bacci, S., Gnaldi, M., and Bartolucci, F. (2015). Assessing user satisfaction in the era of user experience: Comparison of the sus, umux, and umux-lite as a function of product experience. *International Journal of Human-Computer Interaction*, 31(8):484–495. 160, 245
- [Boyandin et al., 2011] Boyandin, I., Bertini, E., Bak, P., and Lalanne, D. (2011). Flowstrates: An approach for visual exploration of temporal origin-destination data. In *Computer Graphics Forum*, volume 30, pages 971–980. Wiley Online Library. 42, 43, 66, 245
- [Brewer et al., 2000] Brewer, I., MacEachren, A. M., Abdo, H., Gundrum, J., and Otto, G. (2000). Collaborative geographic visualization: Enabling shared understanding of environmental processes. In *IEEE Symposium on Information Visualization 2000. INFOVIS 2000. Proceedings*, pages 137–141. IEEE. 238, 245
- [Brooke, 1996] Brooke, J. (1996). SUS: a “quick and dirty” usability. *Usability evaluation in industry*, page 189. 159, 245, 280

- [[Buchroithner et al., 2010](#)] Buchroithner, M., HABERMANN, K., and Gruendemann, T. (2010). True 3d visualization of mountainous terrain by means of lenticular foil technology. In *4th ICA Mountain Cartography Workshop*, pages 125–135. 129, 246
- [[Büschel et al., 2016](#)] Büschel, W., Reipschläger, P., and Dachselt, R. (2016). Improving 3D Visualizations: Exploring Spatial Interaction with Mobile Devices. In *Proceedings of the 2016 ACM Companion on Interactive Surfaces and Spaces, ISS '16 Companion*, pages 63–69, New York, NY, USA. ACM. 6, 76, 246
- [[Büschel et al., 2017](#)] Büschel, W., Reipschläger, P., Langner, R., and Dachselt, R. (2017). Investigating the use of spatial interaction for 3d data visualization on mobile devices. In *Proceedings of the 2017 ACM International Conference on Interactive Surfaces and Spaces*, pages 62–71. ACM. 77, 246
- [[CEREMA, 2010](#)] CEREMA (2010). Enquête ménages déplacements, grenoble / grande région grenobloise (emd, grenoble / grande région grenobloise). Syndicat mixte des transports en commun de l'agglomération grenobloise (producteurs), ADISP (diffuseur). 90, 246
- [[CEREMA, 2015](#)] CEREMA (2015). Enquête ménages déplacements, lyon / aire métropolitaine lyonnaise (emd, lyon / aire métropolitaine lyonnaise). Syndicat mixte des transports pour le Rhône et l'agglomération lyonnaise (producteurs), ADISP (diffuseur). 90, 246
- [[CEREMA, 2017](#)] CEREMA (2017). Enquête mobilité (EMC²) 2018 - Rennes / Île-et-Vilaine. 90, 246
- [[Certu, 2013](#)] Certu (2013). Les enquêtes déplacements “standard certu”. https://www.cnis.fr/wp-content/uploads/2017/12/DPR_2013_2e_reunion_COM_territoires_enquetes_deplacements_certu.pdf. Accessed on 29th July 2020. 90, 246
- [[Chegini et al., 2019](#)] Chegini, M., Andrews, K., Schreck, T., and Sourin, A. (2019). Multiple linked-view exploration on large displays facilitated by a secondary handheld device. In *International Workshop on Advanced Image Technology (IWAIT) 2019*, volume 11049, page 110490H. International Society for Optics and Photonics. 239, 246
- [[Chen et al., 2011](#)] Chen, J., Shaw, S. L., Yu, H., Lu, F., Chai, Y., and Jia, Q. (2011). Exploratory data analysis of activity diary data: A space-time GIS approach. *Journal of Transport Geography*, 19(3):394–404. 5, 19, 57, 58, 66, 126, 246

- [[Chen et al., 2015](#)] Chen, S., Yuan, X., Wang, Z., Guo, C., Liang, J., Wang, Z., Zhang, X. L., and Zhang, J. (2015). Interactive visual discovering of movement patterns from sparsely sampled geo-tagged social media data. *IEEE transactions on visualization and computer graphics*, 22(1):270–279. 5, 40, 61, 62, 66, 247
- [[Chen et al., 2018](#)] Chen, W., Xia, J., Wang, X., Wang, Y., Chen, J., and Chang, L. (2018). Relationlines: Visual reasoning of egocentric relations from heterogeneous urban data. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(1):1–21. 5, 55, 66, 247
- [[Cochey and Tabaka, 2007](#)] Cochey, E. and Tabaka, K. (2007). Modes de représentation des trajectoires quotidiennes des habitants. In *Huitièmes Rencontres de Théo Quant*, pages http–thema. 6, 96, 247
- [[Conover et al., 1981](#)] Conover, W. J., Johnson, M. E., and Johnson, M. M. (1981). A comparative study of tests for homogeneity of variances, with applications to the outer continental shelf bidding data. *Technometrics*, 23(4):351–361. 164, 247
- [[Cordeil et al., 2017](#)] Cordeil, M., Bach, B., Li, Y., Wilson, E., and Dwyer, T. (2017). Design space for spatio-data coordination: Tangible interaction devices for immersive information visualisation. In *2017 IEEE Pacific Visualization Symposium (PacificVis)*, pages 46–50. IEEE. 235, 247
- [[Demšar and Virrantaus, 2010](#)] Demšar, U. and Virrantaus, K. (2010). Space–time density of trajectories: exploring spatio-temporal patterns in movement data. *International Journal of Geographical Information Science*, 24(10):1527–1542. 236, 247
- [[Dickmann, 2010](#)] Dickmann, F. (2010). The potential of the lenticular foil technique for thematic cartography. *The Cartographic Journal*, 47(3):250–256. 8, 129, 130, 247
- [[Dupin, 1826](#)] Dupin, C. (1826). Carte figurative de l’instruction populaire de la france. http://math.yorku.ca/SCS/Gallery/images/dupin1826-map_200.jpg, Domaine public, <https://commons.wikimedia.org/w/index.php?curid=29383521>. 3, 22, 247
- [[Dupin, 1827](#)] Dupin, C. (1827). *Forces productives et commerciales de la France*, volume 1. Bachelier. 22, 247
- [[Ellis and Dix, 2006](#)] Ellis, G. and Dix, A. (2006). An explorative analysis of user evaluation studies in information visualisation. In *Proceedings of the 2006*

- AVI workshop on BEyond time and errors: novel evaluation methods for information visualization*, pages 1–7. 31, 81, 83, 226, 237, 247
- [[Encyclopædia Britannica, 2017](#)] Encyclopædia Britannica, E. (2017). Cartography. <https://www.britannica.com/science/cartography>. Accessed on June 3rd, 2020. 21, 248
- [[Ericsson and Simon, 1984](#)] Ericsson, K. A. and Simon, H. A. (1984). *Protocol analysis: Verbal reports as data*. the MIT Press. 82, 248
- [[Fasang and Liao, 2014](#)] Fasang, A. E. and Liao, T. F. (2014). Visualizing sequences in the social sciences. *Sociological Methods & Research*, 43(4):643–676. 124, 248
- [[Ferreira et al., 2013](#)] Ferreira, N., Poco, J., Vo, H. T., Freire, J., and Silva, C. T. (2013). Visual exploration of big spatio-temporal urban data: A study of new york city taxi trips. *IEEE transactions on visualization and computer graphics*, 19(12):2149–2158. 39, 248
- [[Few and Edge, 2007](#)] Few, S. and Edge, P. (2007). Dashboard confusion revisited. *Perceptual Edge*, pages 1–6. 30, 248
- [[Filho et al., 2020](#)] Filho, J. A. W., Stuerzlinger, W., and Nedel, L. (2020). Evaluating an immersive space-time cube geovisualization for intuitive trajectory data exploration. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):514–524. 30, 235, 239, 248
- [[Fischer, 2018](#)] Fischer, A. J. (2018). *Developing and evaluating a geographic information dashboard to improve spatial task performance*. PhD thesis, Kansas State University, Department of Geography. 31, 248
- [[Fish et al., 2011](#)] Fish, C., Goldsberry, K. P., and Battersby, S. (2011). Change blindness in animated choropleth maps: an empirical study. *Cartography and Geographic Information Science*, 38(4):350–362. 30, 129, 231, 248
- [[Fogtmann et al., 2008](#)] Fogtmann, M. H., Fritsch, J., and Kortbek, K. J. (2008). Kinesthetic interaction: revealing the bodily potential in interaction design. In *Proceedings of the 20th Australasian conference on computer-human interaction: designing for habitus and habitat*, pages 89–96. 130, 248
- [[Forsell and Cooper, 2014](#)] Forsell, C. and Cooper, M. (2014). An introduction and guide to evaluation of visualization techniques through user studies. In *Handbook of human centric visualization*, pages 285–313. Springer. 159, 248

- [[Fried et al., 1977](#)] Fried, M., Havens, J., and Thall, M. (1977). Travel behavior-a synthesized theory. Technical report, Department of Psychology, Boston College, United States. 19, 249
- [[Friedman, 1937](#)] Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association*, 32(200):675–701. 165, 249
- [[Fröhlich et al., 2007](#)] Fröhlich, P., Simon, R., Baillie, L., Roberts, J., and Murray-Smith, R. (2007). Mobile spatial interaction. In *CHI'07 Extended Abstracts on Human Factors in Computing Systems*, pages 2841–2844. 236, 249
- [[Gabadinho et al., 2011](#)] Gabadinho, A., Ritschard, G., Mueller, N. S., and Studer, M. (2011). Analyzing and visualizing state sequences in r with traminer. *Journal of Statistical Software*, 40(4):1–37. 104, 141, 249
- [[Gabadinho et al., 2009a](#)] Gabadinho, A., Ritschard, G., Studer, M., and Müller, N. S. (2009a). Extracting and rendering representative sequences. In *International Joint Conference on Knowledge Discovery, Knowledge Engineering, and Knowledge Management*, pages 94–106. Springer. 106, 249
- [[Gabadinho et al., 2009b](#)] Gabadinho, A., Ritschard, G., Studer, M., and Müller, N. S. (2009b). Mining sequence data in r with the traminer package: A user's guide. *Geneva: Department of Econometrics and Laboratory of Demography, University of Geneva*. 99, 249
- [[Gao, 2015](#)] Gao, S. (2015). Spatio-temporal analytics for exploring human mobility patterns and urban dynamics in the mobile age. *Spatial Cognition & Computation*, 15(2):86–114. 5, 61, 66, 67, 249
- [[Ghasemi and Zahediasl, 2012](#)] Ghasemi, A. and Zahediasl, S. (2012). Normality tests for statistical analysis: a guide for non-statisticians. *International journal of endocrinology and metabolism*, 10(2):486. 164, 249
- [[Giraud and Beauguitte, 2016](#)] Giraud, T. and Beauguitte, L. (2016). *flows: Flow Selection and Analysis*. R package version 1.1.1. 97, 141, 249
- [[Giraud et al., 2016](#)] Giraud, T., Beauguitte, L., and Guérois, M. (2016). Introduction to the flows package. <https://cran.r-project.org/web/packages/flows/vignettes/flows.html>. Accessed on July 27th, 2020. 100, 249
- [[Gonçalves et al., 2016](#)] Gonçalves, T., Afonso, A. P., and Martins, B. (2016). Why not both?—combining 2d maps and 3d space-time cubes for human

- trajectory data visualization. In *Proceedings of the 30th International BCS Human Computer Interaction Conference 30*, pages 1–10. 5, 58, 59, 66, 126, 249
- [[Grandi et al., 2018](#)] Grandi, J. G., Debarba, H. G., Bemdt, I., Nedel, L., and Maciel, A. (2018). Design and assessment of a collaborative 3D interaction technique for handheld augmented reality. In *2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pages 49–56. IEEE. 76, 236, 250
- [[Hägerstrand, 1970](#)] Hägerstrand, T. (1970). What about people in regional science? *Regional Science Association*, 24(1):6–21. 19, 25, 250
- [[Hanson and Hanson, 1981](#)] Hanson, S. and Hanson, P. (1981). The travel-activity patterns of urban residents: dimensions and relationships to sociodemographic characteristics. *Economic geography*, 57(4):332–347. 20, 250
- [[Hardisty, 2009](#)] Hardisty, F. (2009). Geojabber: enabling geo-collaborative visual analysis. *Cartography and Geographic Information Science*, 36(3):267–280. 239, 250
- [[Harrower, 2001](#)] Harrower, M. (2001). Visualizing change: Using cartographic animation to explore remotely-sensed data. *Cartographic Perspectives*, (39):30–42. 128, 250
- [[Harrower and Brewer, 2003](#)] Harrower, M. and Brewer, C. A. (2003). Colorbrewer.org: An online tool for selecting colour schemes for maps. *The Cartographic Journal*, 40(1):27–37. 116, 250
- [[Hart, 2006](#)] Hart, S. G. (2006). Nasa-task load index (nasa-tlx); 20 years later. In *Proceedings of the human factors and ergonomics society annual meeting*, volume 50, pages 904–908. Sage publications Sage CA: Los Angeles, CA. 163, 200, 250
- [[Hart and Staveland, 1988](#)] Hart, S. G. and Staveland, L. E. (1988). Development of nasa-tlx (task load index): Results of empirical and theoretical research. *Advances in psychology*, 52:139–183. 9, 161, 163, 250, 278
- [[Horak et al., 2018](#)] Horak, T., Badam, S. K., Elmqvist, N., and Dachsel, R. (2018). When david meets goliath: Combining smartwatches with a large vertical display for visual data exploration. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–13. 77, 250

- [[Horak et al., 2019](#)] Horak, T., Mathisen, A., Klokmoose, C. N., Dachsel, R., and Elmqvist, N. (2019). Vistribute: Distributing interactive visualizations in dynamic multi-device setups. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pages 1–13. 78, 251
- [[Horton and Wagner, 1969](#)] Horton, F. E. and Wagner, W. E. (1969). A markovian analysis of urban travel behavior: Pattern response by socioeconomic-occupational groups. *Highway Research Record*, 283:19–29. 17, 18, 20, 251
- [[Hothorn et al., 2008](#)] Hothorn, T., Bretz, F., and Westfall, P. (2008). Simultaneous inference in general parametric models. *Biometrical Journal*, 50(3):346–363. 165, 251
- [[Isenberg et al., 2011](#)] Isenberg, P., Elmqvist, N., Scholtz, J., Cernea, D., Ma, K.-L., and Hagen, H. (2011). Collaborative visualization: Definition, challenges, and research agenda. *Information Visualization*, 10(4):310–326. 239, 251
- [[ISO 9241-11:2018, 2018](#)] ISO 9241-11:2018 (2018). Ergonomics of human-system interaction — Part 11: Usability: Definitions and concepts. Standard, International Organization for Standardization, Geneva, CH. 159, 251
- [[Itoh et al., 2016](#)] Itoh, M., Yokoyama, D., and Toyoda, M. (2016). Visual Exploration of Changes in Passenger Flows and Tweets on Mega-City Metro Network. *IEEE Transactions on Big Data*, 2(1):85–99. 4, 48, 49, 66, 251
- [[Jahnke et al., 2017](#)] Jahnke, M., Ding, L., Karja, K., and Wang, S. (2017). Identifying origin/destination hotspots in floating car data for visual analysis of traveling behavior. In *Progress in Location-Based Services 2016*, pages 253–269. Springer. 52, 66, 251
- [[Javed and Elmqvist, 2012](#)] Javed, W. and Elmqvist, N. (2012). Exploring the design space of composite visualization. In *2012 IEEE Pacific Visualization Symposium*, pages 1–8. IEEE. 3, 35, 36, 37, 251
- [[Jiang et al., 2015](#)] Jiang, X., Zheng, C., Tian, Y., and Liang, R. (2015). Large-scale taxi o/d visual analytics for understanding metropolitan human movement patterns. *Journal of Visualization*, 18(2):185–200. 41, 42, 66, 251
- [[Kassambara, 2020](#)] Kassambara, A. (2020). Agglomerative hierarchical clustering. <https://www.datanovia.com/en/lessons/agglomerative-hierarchical-clustering/>. Accessed on July 6th, 2020. 7, 103, 104, 251

- [[Kaufman and Rousseeuw, 2009](#)] Kaufman, L. and Rousseeuw, P. J. (2009). *Finding groups in data: an introduction to cluster analysis*, volume 344. John Wiley & Sons. 104, 252
- [[Keim et al., 2009](#)] Keim, D. A., Mansmann, F., Stoffel, A., and Ziegler, H. (2009). *Visual Analytics*, pages 3341–3346. Springer US, Boston, MA. 38, 252
- [[Kister et al., 2017](#)] Kister, U., Klamka, K., Tominski, C., and Dachsel, R. (2017). GraSp: Combining Spatially-aware Mobile Devices and a Display Wall for Graph Visualization and Interaction. *Computer Graphics Forum*, 36(3):503–514. 6, 73, 74, 236, 252
- [[Klemmer et al., 2006](#)] Klemmer, S. R., Hartmann, B., and Takayama, L. (2006). How bodies matter: five themes for interaction design. In *Proceedings of the 6th conference on Designing Interactive systems*, pages 140–149. ACM. 130, 252
- [[Knight, 2001](#)] Knight, C. (2001). Visualisation effectiveness. In *2001 International Conference on Imaging Science, Systems, and Technology (CISST 2001)*, pages 249–254. 81, 226, 252
- [[Koua and Kraak, 2004](#)] Koua, E. L. and Kraak, M.-J. (2004). A usability framework for the design and evaluation of an exploratory geovisualization environment. In *Proceedings. Eighth International Conference on Information Visualisation, 2004. IV 2004.*, pages 153–158. IEEE. 82, 252
- [[Koylu and Guo, 2017](#)] Koylu, C. and Guo, D. (2017). Design and evaluation of line symbolizations for origin–destination flow maps. *Information Visualization*, 16(4):309–331. 41, 252
- [[Kraak, 2003](#)] Kraak, M. (2003). The space - time cube revisited from a geovisualization perspective. In *ICC 2003 : Proceedings of the 21st international cartographic conference*, pages 1988–1996, New Zealand. International Cartographic Association. 25, 235, 252
- [[Kraak, 2006](#)] Kraak, M.-J. (2006). Why maps matter in giscience. *The Cartographic Journal*, 43(1):82–89. 24, 252
- [[Kraak et al., 1997](#)] Kraak, M.-J., Edsall, R., and MacEachren, A. M. (1997). Cartographic animation and legends for temporal maps: Exploration and or interaction. In *Proceedings of the 18th International Cartographic Conference*, volume 1, pages 253 – 261. Citeseer. 24, 252

- [[Kruskal and Wallis, 1952](#)] Kruskal, W. H. and Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, 47(260):583–621. 165, 253
- [[Kveladze et al., 2015](#)] Kveladze, I., Kraak, M.-J., and Van Elzakker, C. P. (2015). The space-time cube as part of a geovisual analytics environment to support the understanding of movement data. *International Journal of Geographical Information Science*, 29(11):2001–2016. 58, 66, 253
- [[Kwan, 2000](#)] Kwan, M.-P. (2000). Interactive geovisualization of activity-travel patterns using three-dimensional geographical information systems: a methodological exploration with a large data set. *Transportation Research Part C: Emerging Technologies*, 8(1-6):185–203. 25, 253
- [[Langner et al., 2017](#)] Langner, R., Horak, T., and Dachsel, R. (2017). VisTiles: Coordinating and Combining Co-located Mobile Devices for Visual Data Exploration. *IEEE Transactions on Visualization and Computer Graphics*, 24(1):626–636. 77, 78, 253
- [[Langner et al., 2018](#)] Langner, R., Kister, U., and Dachsel, R. (2018). Multiple coordinated views at large displays for multiple users: Empirical findings on user behavior, movements, and distances. *IEEE transactions on visualization and computer graphics*, 25(1):608–618. 6, 72, 73, 239, 253
- [[Le Roux et al., 2017](#)] Le Roux, G., Vallée, J., and Commenges, H. (2017). Social segregation around the clock in the paris region (france). *Journal of Transport Geography*, 59:134–145. 5, 62, 63, 66, 227, 253
- [[Lesnard, 2009](#)] Lesnard, L. (2009). Cost setting in optimal matching to uncover contemporaneous socio-temporal patterns. 7, 104, 105, 253
- [[Lesnard, 2010](#)] Lesnard, L. (2010). Setting cost in optimal matching to uncover contemporaneous socio-temporal patterns. *Sociological Methods & Research*, 38(3):389–419. 104, 105, 253
- [[Lewis et al., 2013](#)] Lewis, J. R., Utesch, B. S., and Maher, D. E. (2013). UMUX-LITE: When there’s no time for the sus. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI ’13, pages 2099–2102, New York, NY, USA. ACM. 160, 253, 291
- [[Li et al., 2018](#)] Li, J., Chen, S., Chen, W., Andrienko, G., and Andrienko, N. (2018). Semantics-space-time cube. a conceptual framework for systematic analysis of texts in space and time. *IEEE transactions on visualization and computer graphics*, 26(4):1789 – 1806. 111, 116, 253

- [[Lopes et al., 2015](#)] Lopes, P., Ion, A., Mueller, W., Hoffmann, D., Jonell, P., and Baudisch, P. (2015). Proprioceptive interaction. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 939–948. 77, 254
- [[Lu et al., 2016](#)] Lu, M., Liang, J., Wang, Z., and Yuan, X. (2016). Exploring od patterns of interested region based on taxi trajectories. *Journal of Visualization*, 19(4):811–821. 4, 47, 66, 254
- [[Lu et al., 2015](#)] Lu, M., Wang, Z., and Yuan, X. (2015). TrajRank: Exploring travel behaviour on a route by trajectory ranking. *IEEE Pacific Visualization Symposium*, 2015-July(July):311–318. 4, 53, 66, 254
- [[Maciel et al., 2010](#)] Maciel, A., Nedel, L. P., Jorge, V. A., Ibiapina, J. M., and Silva, L. F. (2010). Reality cues-based interaction using whole-body awareness. In *Proceedings of the 2010 ACM Symposium on Applied Computing*, pages 1224–1228. ACM. 32, 130, 231, 254
- [[Marilleau, 2005](#)] Marilleau, N. (2005). An agent based meta-model for urban mobility modeling. In *First International Conference on Distributed Frameworks for Multimedia Applications*, pages 168–175. IEEE. 17, 254
- [[McNally and Rindt, 2007](#)] McNally, M. G. and Rindt, C. R. (2007). The activity-based approach. In *Handbook of Transport Modelling: 2nd Edition*, pages 55–73. Emerald Group Publishing Limited. 18, 254
- [[Menin et al., 2018](#)] Menin, A., Chardonnel, S., Davoine, P.-A., and Nedel, L. (2018). Exploring Shifting Densities through a Movement-based Cartographic Interface (Short Paper). In *10th International Conference on Geographic Information Science (GIScience 2018)*, volume 114, pages 48:1–48:6, Melbourne, Australia. 254
- [[Menin et al., 2019a](#)] Menin, A., Chardonnel, S., Davoine, P.-A., and Nedel, L. (2019a). eSTIME: Towards an All-in-One Geovisualization Environment for Daily Mobility Analysis. In *32nd SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*, pages 39–46, Rio de Janeiro, Brazil. 254
- [[Menin et al., 2019b](#)] Menin, A., Chardonnel, S., Davoine, P.-A., Ortega, M., Duble, E., and Nedel, L. (2019b). eSTIME : une approche visuelle, interactive et modulable pour l’analyse multi-points de vue des mobilités quotidiennes. In *SAGEO Spatial Analysis and Geomatics*, Clermont-Ferrand, France. 254
- [[Menin et al., 2020](#)] Menin, A., Chardonnel, S., Davoine, P.-A., Ortega, M., Dublé, E., and Nedel, L. (2020). eSTIME : une approche visuelle, interactive

- et modulable pour l'analyse multi-points de vue des mobilités quotidiennes. *Geomatica*, pages 1–22. 254
- [Mennis et al., 2000] Mennis, J. L., Peuquet, D. J., and Qian, L. (2000). A conceptual framework for incorporating cognitive principles into geographical database representation. *International Journal of Geographical Information Science*, 14(6):501–520. 7, 109, 255
- [Merleau-Ponty, 1996] Merleau-Ponty, M. (1996). *Phenomenology of perception*. Motilal Banarsidass Publishe. 130, 255
- [Merriam-Webster's Collegiate Dictionary, 1828] Merriam-Webster's Collegiate Dictionary (1828). Merriam-Webster Incorporated. Accessed on 14th August, 2020. 30, 255
- [Minard, 1869] Minard, C. (1869). Charles minard's map of napoleon's disastrous russian campaign of 1812. Public Domain, commons.wikimedia.org/w/index.php?curid=297925. 3, 24, 255
- [Mine et al., 1997] Mine, M. R., Brooks Jr, F. P., and Sequin, C. H. (1997). Moving objects in space: exploiting proprioception in virtual-environment interaction. In *Proceedings of the 24th annual conference on Computer graphics and interactive techniques*, pages 19–26. ACM Press/Addison-Wesley Publishing Co. 130, 255
- [Miranda et al., 2016] Miranda, F., Doraiswamy, H., Lage, M., Zhao, K., Gonçalves, B., Wilson, L., Hsieh, M., and Silva, C. T. (2016). Urban pulse: Capturing the rhythm of cities. *IEEE transactions on visualization and computer graphics*, 23(1):791–800. 19, 49, 66, 227, 255
- [Monroe and Dugan, 2015] Monroe, M. and Dugan, C. (2015). Disperse: Enabling Web-Based Visualization in Multi-screen and Multi-user Environments. In *Human-Computer Interaction (INTERACT)*, pages 418–435, Cham. 77, 78, 255
- [Montanari, 2002] Montanari, A. (2002). *Human mobility in a borderless world?*, volume 1. Società geografica italiana. 85, 255
- [Montanari, 2005] Montanari, A. (2005). Human mobility, global change and local development. *Revue belge de géographie (Belgeo)*, (1-2):7–18. 17, 255
- [Ni et al., 2006] Ni, T., Schmidt, G. S., Staadt, O. G., Livingston, M. A., Ball, R., and May, R. (2006). A survey of large high-resolution display technologies, techniques, and applications. In *IEEE Virtual Reality Conference (VR 2006)*, pages 223–236. IEEE. 71, 255

- [[North et al., 2011](#)] North, C., Chang, R., Endert, A., Dou, W., May, R., Pike, B., and Fink, G. (2011). Analytic provenance: process+ interaction+ insight. In *CHI'11 Extended Abstracts on Human Factors in Computing Systems*, pages 33–36. [138](#), [233](#), [256](#)
- [[North and Shneiderman, 1997](#)] North, C. and Shneiderman, B. (1997). A taxonomy of multiple window coordination. Technical report, Human-Computer Interaction Lab, University of Maryland. [35](#), [256](#)
- [[Noulas et al., 2012](#)] Noulas, A., Scellato, S., Lambiotte, R., Pontil, M., and Mascolo, C. (2012). A Tale of Many Cities: Universal Patterns in Human Urban Mobility. *PLOS ONE*, 7(5):1–10. [26](#), [256](#)
- [[Novák and Sýkora, 2007](#)] Novák, J. and Sýkora, L. (2007). A city in motion: time-space activity and mobility patterns of suburban inhabitants and the structuration of the spatial organization of the prague metropolitan area. *Geografiska Annaler: Series B, Human Geography*, 89(2):147–168. [19](#), [256](#)
- [[Nystuen and Dacey, 1961](#)] Nystuen, J. D. and Dacey, M. F. (1961). A graph theory interpretation of nodal regions. In *Papers of the Regional Science Association*, volume 7, pages 29–42. Springer. [100](#), [256](#)
- [[Offner, 2020](#)] Offner, J.-M. (2020). *Anachronismes urbains*. Essai. Presses de Sciences Po, Paris. [27](#), [256](#)
- [[Oliveira et al., 2016](#)] Oliveira, G. N., Sotomayor, J. L., Torchelsen, R. P., Silva, C. T., and Comba, J. L. (2016). Visual analysis of bike-sharing systems. *Computers & Graphics*, 60:119–129. [46](#), [66](#), [256](#)
- [[Otten et al., 2015](#)] Otten, H., Hildebrandt, L., Nagel, T., Dörk, M., and Müller, B. (2015). Are there networks in maps? an experimental visualization of personal movement data. *Personal Visualization: Exploring Data in Everyday Life*, pages 5–7. [26](#), [256](#)
- [[Pahud et al., 2018](#)] Pahud, M., Ofek, E., Riche, N. H., Hurter, C., and Grubert, J. (2018). Mobiles as Portals for Interacting with Virtual Data Visualizations. *arXiv preprint arXiv:1804.03211*. [76](#), [236](#), [256](#)
- [[Paiva Nogueira, 2017](#)] Paiva Nogueira, T. (2017). *A Framework for Automatic Annotation of Semantic Trajectories*. Theses, Université Grenoble Alpes. [40](#), [256](#)
- [[Palsky, 2008](#)] Palsky, G. (2008). Connections and exchanges in European thematic cartography. The case of 19th century choropleth maps. *Belgian Journal of Geography (Belgeo [Online])*, pages 713–426. [22](#), [256](#)

- [[Pas and Koppelman, 1987](#)] Pas, E. I. and Koppelman, F. S. (1987). An examination of the determinants of day-to-day variability in individuals' urban travel behavior. *Transportation*, 14(1):3–20. 18, 257
- [[Pelletier et al., 2009](#)] Pelletier, M.-P., Trépanier, M., and Morency, C. (2009). *Smart card data in public transit planning: a review*. CIRRELT Montreal, Quebec, Canada. 39, 257
- [[Peuquet, 1994](#)] Peuquet, D. J. (1994). It's about time: A conceptual framework for the representation of temporal dynamics in geographic information. *Annals of the Association of American Geographers*, 84(3):441–461. 7, 108, 109, 257
- [[Pietroszek et al., 2015](#)] Pietroszek, K., Wallace, J. R., and Lank, E. (2015). Tilt-casting: 3D Interaction on Large Displays Using a Mobile Device. In *Proceedings of the 28th Annual ACM Symp. on User Interface Software & Technology*, UIST '15, pages 57–62, New York, NY, USA. ACM. 6, 75, 76, 257
- [[Plumlee and Ware, 2006](#)] Plumlee, M. D. and Ware, C. (2006). Zooming versus multiple window interfaces: Cognitive costs of visual comparisons. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 13(2):179–209. 69, 257
- [[Pohlert, 2020](#)] Pohlert, T. (2020). *PMCMRplus: Calculate Pairwise Multiple Comparisons of Mean Rank Sums Extended*. R package version 1.4.4. 165, 257
- [[Pouyanne et al., 2005](#)] Pouyanne, G. et al. (2005). Urban form and travel patterns: an application to the metropolitan area of bordeaux. *Canadian Journal of Regional Science*, 28(1):19–48. 20, 257
- [[Quirk, 2016](#)] Quirk, T. J. (2016). One-way analysis of variance (anova). pages 165–182. 164, 257
- [[R Development Core Team et al., 2011](#)] R Development Core Team, R. et al. (2011). R: A language and environment for statistical computing. R foundation for statistical computing Vienna, Austria. 86, 140, 165, 257
- [[Raghavan et al., 2016](#)] Raghavan, V. V., Gudivada, V. N., Govindaraju, V., and Rao, C. R. (2016). *Cognitive computing: Theory and applications*. Elsevier. 37, 257

- [[Rajabiyazdi et al., 2015](#)] Rajabiyazdi, F., Walny, J., Mah, C., Brosz, J., and Carpendale, S. (2015). Understanding researchers' use of a large, high-resolution display across disciplines. In *Proceedings of the 2015 International Conference on Interactive Tabletops & Surfaces*, pages 107–116. 71, 258
- [[Richard and Rabaud, 2018](#)] Richard, O. and Rabaud, M. (2018). French household travel survey: The next generation. *Transportation Research Procedia*, 32:383 – 393. Transport Survey Methods in the era of big data: facing the challenges. 18, 89, 90, 258
- [[Roberts, 2007](#)] Roberts, J. C. (2007). State of the art: Coordinated & multiple views in exploratory visualization. In *Fifth International Conference on Coordinated and Multiple Views in Exploratory Visualization (CMV 2007)*, pages 61–71. IEEE. 36, 258
- [[Robette, 2011](#)] Robette, N. (2011). *Explorer et décrire les parcours de vie: les typologies de trajectoires*. CEPED. 28, 86, 240, 258
- [[Robinson, 1955](#)] Robinson, A. H. (1955). The 1837 Maps of Henry Drury Harness. *The Geographical Journal*, 121(4):440 – 450. 3, 22, 23, 258
- [[Rubin and Chisnell, 2008](#)] Rubin, J. and Chisnell, D. (2008). *Handbook of usability testing: how to plan, design and conduct effective tests*. John Wiley & Sons. 159, 258
- [[Sammons, 2015](#)] Sammons, J. (2015). Mobile device forensics. In *The Basics of Digital Forensics*, pages 145 – 161. Syngress, 2nd edition. 39, 258
- [[Sauro and Lewis, 2016](#)] Sauro, J. and Lewis, J. R. (2016). *Quantifying the user experience: Practical statistics for user research*. Morgan Kaufmann. 13, 160, 161, 258
- [[Schlich and Axhausen, 2003](#)] Schlich, R. and Axhausen, K. W. (2003). Habitual travel behaviour: evidence from a six-week travel diary. *Transportation*, 30(1):13–36. 19, 258
- [[Shaw and Yu, 2009](#)] Shaw, S. L. and Yu, H. (2009). A GIS-based time-geographic approach of studying individual activities and interactions in a hybrid physical-virtual space. *Journal of Transport Geography*, 17(2):141–149. 3, 25, 26, 258
- [[Shi et al., 2017](#)] Shi, L., Jiang, T., Zhao, Y., Zhang, X., and Lu, Y. (2017). Urban-FACET: Visually Profiling Cities from Mobile Device Recorded Movement Data of Millions of City Residents. Preprint arXiv:1707.04210. 50, 66, 258

- [[Shi et al., 2018](#)] Shi, X., Yu, Z., Chen, J., Xu, H., and Lin, F. (2018). The visual analysis of flow pattern for public bicycle system. *Journal of Visual Languages & Computing*, 45:51 – 60. [3](#), [44](#), [49](#), [66](#), [121](#), [196](#), [259](#)
- [[Shi et al., 2015](#)] Shi, X., Yu, Z., Xu, H., and Chen, J. (2015). Pbikevis: Applied visual analytics for public bicycle system. In *2015 8th International Symposium on Computational Intelligence and Design (ISCID)*, volume 1, pages 490–493. IEEE. [50](#), [66](#), [259](#)
- [[Shneiderman, 1996](#)] Shneiderman, B. (1996). The eyes have it: A task by data type taxonomy for information visualizations. In *Proceedings 1996 IEEE symposium on visual languages*, pages 336–343. IEEE. [69](#), [132](#), [259](#)
- [[Shneiderman and Plaisant, 2006](#)] Shneiderman, B. and Plaisant, C. (2006). Strategies for evaluating information visualization tools: multi-dimensional in-depth long-term case studies. In *Proceedings of the 2006 AVI workshop on BEyond time and errors: novel evaluation methods for information visualization*, pages 1–7. [81](#), [226](#), [259](#)
- [[Shoval and Isaacson, 2007](#)] Shoval, N. and Isaacson, M. (2007). Sequence alignment as a method for human activity analysis in space and time. *Annals of the Association of American geographers*, 97(2):282–297. [5](#), [57](#), [59](#), [66](#), [259](#)
- [[Sobral et al., 2019](#)] Sobral, T., Galvão, T., and Borges, J. (2019). Visualization of urban mobility data from intelligent transportation systems. *Sensors*, 19(2):332. [65](#), [228](#), [259](#)
- [[Spindler et al., 2010](#)] Spindler, M., Tominski, C., Schumann, H., and Dachselt, R. (2010). Tangible views for information visualization. In *ACM International Conference on Interactive Tabletops and Surfaces*, pages 157–166. ACM. [76](#), [259](#)
- [[Student, 1908](#)] Student (1908). The probable error of a mean. *Biometrika*, pages 1–25. [164](#), [259](#)
- [[Tabaka et al., 2020](#)] Tabaka, K., Duché, S., Menin, A., and Chardonnel, S. (2020). Metropolitan mobility and daily activities diversities and constraints: the Grenoble urban area case. In *CIST2020 - Population, temps, territoires*, Paris, France. [259](#)
- [[Thrower, 1959](#)] Thrower, N. J. W. (1959). Animated Cartography. *The Professional Geographer*, 11(6):9 – 12. [24](#), [259](#)
- [[Tobler, 1970](#)] Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic geography*, 46(sup1):234 – 240. [25](#), [259](#)

- [Tominski et al., 2012] Tominski, C., Schumann, H., Andrienko, G., and Andrienko, N. (2012). Stacking-based visualization of trajectory attribute data. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2565–2574. 5, 54, 66, 260
- [Tsandilas et al., 2015] Tsandilas, T., Bezerianos, A., and Jacob, T. (2015). Sketchsliders: Sketching widgets for visual exploration on wall displays. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 3255–3264. 6, 75, 260
- [Tversky et al., 2002] Tversky, B., Morrison, J. B., and Betrancourt, M. (2002). Animation: can it facilitate? *International journal of human-computer studies*, 57(4):247–262. 128, 260
- [U.S. Dept. of Health and Human Services, 2006] U.S. Dept. of Health and Human Services (2006). The Research-Based Web Design & Usability Guidelines, Expanded edition – System Usability Scale (SUS). <https://www.usability.gov/how-to-and-tools/methods/system-usability-scale.html>. Accessed on 10th August, 2020. 159, 260
- [Vrotsou et al., 2010] Vrotsou, K., Forsell, C., and Cooper, M. (2010). 2d and 3d representations for feature recognition in time geographical diary data. *Information Visualization*, 9(4):263–276. 5, 56, 57, 66, 260
- [Wagman, 2009] Wagman, D. (2009). Urban maps gives a vintage printing technique a high-tech revival. <https://www.directionsmag.com/article/3272>. Accessed on April 4th, 2020. 129, 260
- [Wang et al., 2017] Wang, F., Chen, W., Zhao, Y., Gu, T., Gao, S., and Bao, H. (2017). Adaptively Exploring Population Mobility Patterns in Flow Visualization. *IEEE Transactions on Intelligent Transportation Systems*, 18(8):2250–2259. 64, 66, 260
- [Wang, 2016] Wang, Y. (2016). A visual analysis system for exploring passenger flow information at multiple levels. In *2016 IEEE 20th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 363–368. IEEE. 3, 44, 45, 66, 260
- [Wang et al., 2013] Wang, Z., Lu, M., Yuan, X., Zhang, J., and Van De Wetering, H. (2013). Visual traffic jam analysis based on trajectory data. *IEEE transactions on visualization and computer graphics*, 19(12):2159–2168. 64, 66, 260
- [Ward, 1963] Ward, J. J. H. (1963). Hierarchical grouping to optimize an objective function. 105, 260

- [[Ware, 2019](#)] Ware, C. (2019). *Information visualization: perception for design*. Morgan Kaufmann. 235, 261
- [[Weiser, 1999](#)] Weiser, M. (1999). The computer for the 21st century. *ACM SIGMOBILE mobile computing and communications review*, 3(3):3–11. 79, 261
- [[Wickham, 2011](#)] Wickham, H. (2011). The split-apply-combine strategy for data analysis. *Journal of Statistical Software*, 40(1):1–29. 165, 261
- [[Wickham, 2016](#)] Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. 165, 261
- [[Wickham, 2017](#)] Wickham, H. (2017). *tidyverse: Easily Install and Load the 'Tidyverse'*. R package version 1.2.1. 141, 165, 261
- [[Wilcoxon, 1945](#)] Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics Bulletin*, 1(6):80–83. 165, 261
- [[Wilson and Foglia, 2017](#)] Wilson, R. A. and Foglia, L. (2017). Embodied cognition. In Zalta, E. N., editor, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, spring 2017 edition. 130, 261
- [[Wu et al., 2015](#)] Wu, W., Xu, J., Zeng, H., Zheng, Y., Qu, H., Ni, B., Yuan, M., and Ni, L. M. (2015). Telcovis: Visual exploration of co-occurrence in urban human mobility based on telco data. *IEEE transactions on visualization and computer graphics*, 22(1):935–944. 5, 64, 65, 66, 261
- [[Wu et al., 2017](#)] Wu, W., Zheng, Y., Cao, N., Zeng, H., Ni, B., Qu, H., and Ni, L. M. (2017). Mobiseg: Interactive region segmentation using heterogeneous mobility data. In *2017 IEEE Pacific Visualization Symposium (PacificVis)*, pages 91–100. IEEE. 4, 47, 48, 66, 261
- [[Xu et al., 2015](#)] Xu, K., Attfield, S., Jankun-Kelly, T., Wheat, A., Nguyen, P. H., and Selvaraj, N. (2015). Analytic provenance for sensemaking: A research agenda. *IEEE computer graphics and applications*, 35(3):56–64. 138, 261
- [[Yan et al., 2018](#)] Yan, Y., Tao, Y., Xu, J., Ren, S., and Lin, H. (2018). Visual analytics of bike-sharing data based on tensor factorization. *Journal of Visualization*, 21(3):495–509. 4, 26, 50, 66, 261
- [[Yang et al., 2016](#)] Yang, Y., Dwyer, T., Goodwin, S., and Marriott, K. (2016). Many-to-many geographically-embedded flow visualisation: An evaluation. *IEEE transactions on visualization and computer graphics*, 23(1):411–420. 42, 43, 66, 261

- [Yu and Shaw, 2004] Yu, H. and Shaw, S.-L. (2004). Representing and visualizing travel diary data: A spatio-temporal gis approach. In *2004 ESRI International User Conference*, pages 1–13. 18, 262
- [Yu et al., 2015] Yu, L., Wu, W., Li, X., Li, G., Ng, W. S., Ng, S.-K., Huang, Z., Arunan, A., and Watt, H. M. (2015). iviztrans: Interactive visual learning for home and work place detection from massive public transportation data. In *2015 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pages 49–56. IEEE. 5, 60, 61, 66, 67, 236, 262
- [Zagermann et al., 2020] Zagermann, J., Pfeil, U., von Bauer, P., Fink, D., and Reiterer, H. (2020). "It's in my other hand!"—Studying the Interplay of Interaction Techniques and Multi-Tablet Activities. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13. 79, 262
- [Zeng et al., 2014] Zeng, W., Fu, C. W., Arisona, S. M., Erath, A., and Qu, H. (2014). Visualizing mobility of public transportation system. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):1833–1842. 4, 46, 49, 66, 262
- [Zeng et al., 2017] Zeng, W., Fu, C.-W., Arisona, S. M., Schubiger, S., Burkhard, R., and Ma, K.-L. (2017). Visualizing the relationship between human mobility and points of interest. *IEEE Transactions on Intelligent Transportation Systems*, 18(8):2271–2284. 4, 52, 53, 66, 118, 262
- [Zhang and Wang, 2017] Zhang, X. and Wang, Q. (2017). Peoplevis: A visual analysis system for mining travel behavior. In *2017 IEEE 21st International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 463–468. IEEE. 56, 66, 262
- [Zhao et al., 2008] Zhao, J., Forer, P., and Harvey, A. S. (2008). Activities, ringmaps and geovisualization of large human movement fields. *Information Visualization*, 7(3-4):198–209. 118, 262
- [Zheng et al., 2016] Zheng, Y., Wu, W., Zeng, H., Cao, N., Qu, H., Yuan, M., Zeng, J., and Ni, L. M. (2016). TelcoFlow: Visual exploration of collective behaviors based on telco data. *Proceedings - 2016 IEEE International Conference on Big Data, Big Data 2016*, pages 843–852. 5, 39, 62, 63, 66, 262

APPENDIX A

**Typology of Activity Programs:
Characteristics of Individuals**

Grenoble: Socio-demographic aspects of individuals.							
	Category	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Age	05-17	86 (9.89%)	258 (4.88%)	2506 (78.85%)	15 (0.36%)	37 (13.41%)	1 (0.09%)
	18-24	53 (6.09%)	312 (5.90%)	596 (18.75%)	237 (5.74%)	66 (23.91%)	50 (4.64%)
	25-34	90 (10.34%)	526 (9.94%)	56 (1.76%)	851 (20.61%)	55 (19.93%)	146 (13.54%)
	35-49	146 (16.78%)	863 (16.31%)	15 (0.47%)	1909 (46.23%)	63 (22.83%)	521 (48.33%)
	50-64	250 (28.74%)	1477 (27.92%)	1 (0.03%)	1096 (26.54%)	50 (18.12%)	350 (32.47%)
	65+	245 (28.16%)	1854 (35.05%)	4 (0.13%)	21 (0.51%)	5 (1.81%)	10 (0.93%)
Gender	female	452 (51.95%)	2985 (56.43%)	1549 (48.74%)	1902 (46.06%)	104 (37.68%)	472 (43.78%)
	male	418 (48.05%)	2305 (43.57%)	1629 (51.26%)	2227 (53.94%)	172 (62.32%)	606 (56.22%)
Working Status	full-time employment	197 (22.64%)	812 (15.35%)	2 (0.06%)	3433 (83.14%)	151 (54.71%)	831 (77.09%)
	internship	5 (0.57%)	18 (0.34%)	38 (1.20%)	47 (1.14%)	3 (1.09%)	5 (0.46%)
	other	18 (2.07%)	224 (4.23%)	-	-	2 (0.72%)	-
	part-time employment	67 (7.70%)	354 (6.69%)	3 (0.09%)	585 (14.17%)	23 (8.33%)	232 (21.52%)
	retired	353 (40.57%)	2531 (47.84%)	4 (0.13%)	18 (0.44%)	8 (2.90%)	6 (0.56%)
	school student	85 (9.77%)	267 (5.05%)	2613 (82.22%)	2 (0.05%)	44 (15.94%)	-
	stay at home	50 (5.75%)	496 (9.38%)	1 (0.03%)	-	2 (0.72%)	-
	unemployed	76 (8.74%)	423 (8.00%)	2 (0.06%)	6 (0.15%)	11 (3.99%)	2 (0.19%)
	university student	19 (2.18%)	165 (3.12%)	515 (16.21%)	38 (0.92%)	32 (11.59%)	2 (0.19%)
Socio-professional Category	apprentices	5 (0.57%)	18 (0.34%)	38 (1.20%)	47 (1.14%)	3 (1.09%)	5 (0.46%)
	blue collar workers	136 (15.63%)	981 (18.54%)	-	481 (11.65%)	33 (11.96%)	287 (26.62%)
	business owners and shopkeepers	51 (5.86%)	304 (5.75%)	-	213 (5.16%)	20 (7.25%)	54 (5.01%)
	employees	164 (18.85%)	1353 (25.58%)	2 (0.06%)	938 (22.72%)	54 (19.57%)	330 (30.61%)
	executives and professionals	170 (19.54%)	699 (13.21%)	4 (0.13%)	1315 (31.85%)	32 (11.59%)	145 (13.45%)
	farmers	15 (1.72%)	134 (2.53%)	-	27 (0.65%)	2 (0.72%)	13 (1.21%)
	no professional activity	149 (17.13%)	841 (15.90%)	3129 (98.46%)	40 (0.97%)	81 (29.35%)	4 (0.37%)
	technicians and associate professionals	178 (20.46%)	957 (18.09%)	5 (0.16%)	1067 (25.84%)	51 (18.48%)	240 (22.26%)

Table A.1: Socio-demographic aspects of surveyed individuals in the urban area of Grenoble per group of the typology of activity programs.

Grenoble: Usage frequency of private transportation modes.							
	Frequency	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Car/van as a driver	everyday	457 (52.53%)	2371 (44.82%)	135 (4.25%)	3159 (76.51%)	146 (52.90%)	815 (75.60%)
	never	198 (22.76%)	1326 (25.07%)	2779 (87.44%)	274 (6.64%)	77 (27.90%)	104 (9.65%)
	rarely	21 (2.41%)	185 (3.50%)	56 (1.76%)	114 (2.76%)	10 (3.62%)	25 (2.32%)
	twice-month	26 (2.99%)	181 (3.42%)	52 (1.64%)	122 (2.95%)	7 (2.54%)	23 (2.13%)
	twice-week	166 (19.08%)	1218 (23.02%)	123 (3.87%)	459 (11.12%)	29 (10.51%)	110 (10.20%)
Car/van as a passenger	everyday	119 (13.68%)	534 (10.09%)	1231 (38.74%)	210 (5.09%)	40 (14.49%)	63 (5.84%)
	never	155 (17.82%)	1112 (21.02%)	245 (7.71%)	1375 (33.30%)	57 (20.65%)	342 (31.73%)
	rarely	286 (32.87%)	1544 (29.19%)	382 (12.02%)	1472 (35.65%)	85 (30.80%)	360 (33.40%)
	twice-month	104 (11.95%)	688 (13.01%)	284 (8.94%)	431 (10.44%)	35 (12.68%)	129 (11.97%)
	twice-week	204 (23.45%)	1403 (26.52%)	1003 (31.56%)	640 (15.50%)	52 (18.84%)	183 (16.98%)
Two-wheeled motorcycle	everyday	4 (0.46%)	24 (0.45%)	17 (0.53%)	46 (1.11%)	5 (1.81%)	14 (1.30%)
	never	813 (93.45%)	5060 (95.65%)	3021 (95.06%)	3723 (90.17%)	241 (87.32%)	951 (88.22%)
	rarely	21 (2.41%)	101 (1.91%)	52 (1.64%)	173 (4.19%)	14 (5.07%)	63 (5.84%)
	twice-month	14 (1.61%)	48 (0.91%)	25 (0.79%)	86 (2.08%)	5 (1.81%)	26 (2.41%)
	twice-week	16 (1.84%)	48 (0.91%)	30 (0.94%)	100 (2.42%)	4 (1.45%)	23 (2.13%)
Bicycle	everyday	36 (4.14%)	230 (4.35%)	203 (6.39%)	281 (6.81%)	15 (5.43%)	54 (5.01%)
	never	524 (60.23%)	3383 (63.95%)	1352 (42.54%)	2295 (55.58%)	160 (57.97%)	638 (59.18%)
	rarely	185 (21.26%)	1035 (19.57%)	894 (28.13%)	975 (23.61%)	55 (19.93%)	243 (22.54%)
	twice-month	60 (6.90%)	260 (4.91%)	323 (10.16%)	280 (6.78%)	15 (5.43%)	68 (6.31%)
	twice-week	63 (7.24%)	373 (7.05%)	373 (11.74%)	297 (7.19%)	24 (8.70%)	74 (6.86%)

Table A.2: Usage frequency of private transportation modes of the surveyed individuals of the urban area of Grenoble per group in the typology of activity programs.

Grenoble: Usage frequency of the public transportation system.							
Frequency	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	
TAG ⁱ	everyday	73 (8.39%)	456 (8.62%)	779 (24.51%)	385 (9.32%)	46 (16.67%)	115 (10.67%)
	never	432 (49.66%)	2678 (50.62%)	1344 (42.29%)	2220 (53.77%)	127 (46.01%)	640 (59.37%)
	rarely	170 (19.54%)	966 (18.26%)	572 (18.00%)	901 (21.82%)	50 (18.12%)	189 (17.53%)
	twice-month	91 (10.46%)	557 (10.53%)	231 (7.27%)	385 (9.32%)	22 (7.97%)	89 (8.26%)
	twice-week	102 (11.72%)	624 (11.80%)	219 (6.89%)	237 (5.74%)	24 (8.70%)	44 (4.08%)
TER ⁱⁱ	everyday	10 (1.15%)	36 (0.68%)	48 (1.51%)	142 (3.44%)	1 (0.36%)	28 (2.60%)
	never	631 (72.53%)	4047 (76.50%)	2391 (75.24%)	3083 (74.67%)	174 (63.04%)	855 (79.31%)
	rarely	185 (21.26%)	983 (18.58%)	514 (16.17%)	733 (17.75%)	65 (23.55%)	161 (14.94%)
	twice-month	24 (2.76%)	154 (2.91%)	129 (4.06%)	135 (3.27%)	21 (7.61%)	25 (2.32%)
	twice-week	18 (2.07%)	61 (1.15%)	63 (1.98%)	35 (0.85%)	8 (2.90%)	8 (0.74%)
Tramway only	everyday	53 (6.09%)	353 (6.67%)	538 (16.93%)	289 (7.00%)	30 (10.87%)	83 (7.70%)
	never	434 (49.89%)	2820 (53.31%)	1491 (46.92%)	2245 (54.37%)	128 (46.38%)	643 (59.65%)
	rarely	196 (22.53%)	1063 (20.09%)	659 (20.74%)	974 (23.59%)	66 (23.91%)	216 (20.04%)
	twice-month	92 (10.57%)	512 (9.68%)	224 (7.05%)	365 (8.84%)	22 (7.97%)	89 (8.26%)
	twice-week	93 (10.69%)	533 (10.08%)	233 (7.33%)	255 (6.18%)	23 (8.33%)	46 (4.27%)
TRANSISERE ⁱⁱⁱ	everyday	14 (1.61%)	62 (1.17%)	569 (17.90%)	103 (2.49%)	9 (3.26%)	19 (1.76%)
	never	710 (81.61%)	4418 (83.52%)	2072 (65.20%)	3545 (85.86%)	214 (77.54%)	960 (89.05%)
	rarely	106 (12.18%)	553 (10.45%)	355 (11.17%)	370 (8.96%)	32 (11.59%)	72 (6.68%)
	twice-month	24 (2.76%)	168 (3.18%)	82 (2.58%)	81 (1.96%)	8 (2.90%)	23 (2.13%)
	twice-week	14 (1.61%)	80 (1.51%)	67 (2.11%)	29 (0.70%)	6 (2.17%)	3 (0.28%)
Other PTS	everyday	3 (0.34%)	46 (0.87%)	175 (5.51%)	34 (0.82%)	5 (1.81%)	17 (1.58%)
	never	797 (91.61%)	4757 (89.92%)	2669 (83.98%)	3806 (92.18%)	235 (85.14%)	996 (92.39%)
	rarely	46 (5.29%)	322 (6.09%)	202 (6.36%)	223 (5.40%)	18 (6.52%)	49 (4.55%)
	twice-month	11 (1.26%)	74 (1.40%)	49 (1.54%)	33 (0.80%)	6 (2.17%)	12 (1.11%)
	twice-week	11 (1.26%)	82 (1.55%)	50 (1.57%)	32 (0.78%)	5 (1.81%)	3 (0.28%)

ⁱ The *Société d'économie mixte des transports publics de l'agglomération grenobloise* (SÉMITAG) operates its services, which includes bus services and tramway (i.e. the tram system), under the TAG brand (<https://www.tag.fr/>).

ⁱⁱ The *Transport Express Régional* (TER) denote the rail service run by the regional council of France (<https://www.sncf.com/fr/offres-voyageurs/voyager-en-train/ter>).

ⁱⁱⁱ The *Réseau interurbain de l'Isère* (TRANSISERE) is the interurban transport network of the Isère department, in the Auvergne-Rhône-Alpes region (<https://www.transisere.fr/>).

Table A.3: Usage frequency of public transportation system (PTS) of the surveyed individuals of the urban area of Grenoble per group in the typology of activity programs.

Lyon: Socio-demographic aspects of individuals.

Categories		Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Age	05-17	210 (2.21%)	5 (0.07%)	4335 (78.08%)	47 (19.26%)	3 (0.20%)	36 (3.24%)
	18-24	657 (6.92%)	396 (5.45%)	1105 (19.90%)	87 (35.66%)	77 (5.02%)	76 (6.85%)
	25-34	935 (9.85%)	1549 (21.32%)	99 (1.78%)	36 (14.75%)	254 (16.55%)	118 (10.63%)
	35-49	1511 (15.91%)	3142 (43.25%)	10 (0.18%)	15 (6.15%)	652 (42.48%)	208 (18.74%)
	50-64	2275 (23.95%)	2113 (29.09%)	2 (0.04%)	33 (13.52%)	530 (34.53%)	303 (27.30%)
	65+	3909 (41.16%)	59 (0.81%)	1 (0.02%)	26 (10.66%)	19 (1.24%)	369 (33.24%)
Gender	female	5442 (57.30%)	3489 (48.03%)	2734 (49.24%)	130 (53.28%)	733 (47.75%)	554 (49.91%)
	male	4055 (42.70%)	3775 (51.97%)	2818 (50.76%)	114 (46.72%)	802 (52.25%)	556 (50.09%)
Working Status	full-time employment	1693 (17.83%)	6339 (87.27%)	5 (0.09%)	61 (25.00%)	1238 (80.65%)	288 (25.95%)
	internship	25 (0.26%)	33 (0.45%)	95 (1.71%)	4 (1.64%)	8 (0.52%)	1 (0.09%)
	other	214 (2.25%)	-	-	1 (0.41%)	-	26 (2.34%)
	part-time employment	578 (6.09%)	820 (11.29%)	-	12 (4.92%)	264 (17.20%)	64 (5.77%)
	retired	4825 (50.81%)	33 (0.45%)	1 (0.02%)	35 (14.34%)	15 (0.98%)	487 (43.87%)
	school student	201 (2.12%)	1 (0.01%)	4424 (79.68%)	49 (20.08%)	-	34 (3.06%)
	stay at home	644 (6.78%)	-	-	3 (1.23%)	-	49 (4.41%)
	unemployed	924 (9.73%)	7 (0.10%)	3 (0.05%)	22 (9.02%)	3 (0.20%)	129 (11.62%)
	university student	393 (4.14%)	31 (0.43%)	1024 (18.44%)	57 (23.36%)	7 (0.46%)	32 (2.88%)
Socio-professional Category	blue collar workers	1131 (11.91%)	576 (7.93%)	1 (0.02%)	19 (7.79%)	279 (18.18%)	138 (12.43%)
	business owners and shopkeepers	263 (2.77%)	226 (3.11%)	-	2 (0.82%)	32 (2.08%)	40 (3.60%)
	employees	1757 (18.50%)	1102 (15.17%)	-	20 (8.20%)	316 (20.59%)	174 (15.68%)
	executives and professionals	1049 (11.05%)	1711 (23.55%)	6 (0.11%)	17 (6.97%)	129 (8.40%)	166 (14.95%)
	farmers	23 (0.24%)	6 (0.08%)	-	-	2 (0.13%)	1 (0.09%)
	no professional activity	960 (10.11%)	43 (0.59%)	4067 (73.25%)	93 (38.11%)	10 (0.65%)	103 (9.28%)
	technicians and associate professionals	1187 (12.50%)	1409 (19.40%)	2 (0.04%)	22 (9.02%)	231 (15.05%)	149 (13.42%)

Table A.4: Socio-demographic aspects of surveyed individuals in the urban area of Lyon per group of the typology of activity programs.

Lyon: Usage frequency of private transportation modes.							
	Frequency	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Bus	everyday	36 (0.38%)	25 (0.34%)	491 (8.84%)	6 (2.46%)	9 (0.59%)	9 (0.81%)
	never	3295 (34.70%)	2546 (35.05%)	1080 (19.45%)	62 (25.41%)	611 (39.80%)	357 (32.16%)
	rarely	446 (4.70%)	232 (3.19%)	310 (5.58%)	11 (4.51%)	58 (3.78%)	53 (4.77%)
	twice-month	103 (1.08%)	20 (0.28%)	45 (0.81%)	2 (0.82%)	5 (0.33%)	10 (0.90%)
	twice-week	42 (0.44%)	8 (0.11%)	52 (0.94%)	4 (1.64%)	4 (0.26%)	5 (0.45%)
Car/Van as driver	everyday	4042 (42.56%)	5094 (70.13%)	184 (3.31%)	81 (33.20%)	1130 (73.62%)	544 (49.01%)
	never	2471 (26.02%)	796 (10.96%)	5008 (90.20%)	116 (47.54%)	197 (12.83%)	250 (22.52%)
	rarely	428 (4.51%)	374 (5.15%)	127 (2.29%)	10 (4.10%)	37 (2.41%)	43 (3.87%)
	twice-month	488 (5.14%)	311 (4.28%)	81 (1.46%)	10 (4.10%)	44 (2.87%)	60 (5.41%)
	twice-week	2060 (21.69%)	685 (9.43%)	141 (2.54%)	27 (11.07%)	125 (8.14%)	212 (19.10%)
Car/Van as passenger	everyday	606 (6.38%)	269 (3.70%)	1921 (34.60%)	33 (13.52%)	85 (5.54%)	84 (7.57%)
	never	2582 (27.19%)	2800 (38.55%)	713 (12.84%)	41 (16.80%)	558 (36.35%)	314 (28.29%)
	rarely	2748 (28.94%)	2265 (31.18%)	786 (14.16%)	69 (28.28%)	455 (29.64%)	311 (28.02%)
	twice-month	1383 (14.56%)	893 (12.29%)	683 (12.30%)	38 (15.57%)	196 (12.77%)	157 (14.14%)
	twice-week	2170 (22.85%)	1033 (14.22%)	1438 (25.90%)	63 (25.82%)	239 (15.57%)	243 (21.89%)
Bicycle	everyday	264 (2.78%)	315 (4.34%)	196 (3.53%)	11 (4.51%)	47 (3.06%)	37 (3.33%)
	never	6846 (72.09%)	4666 (64.23%)	3174 (57.17%)	147 (60.25%)	1039 (67.69%)	761 (68.56%)
	rarely	1288 (13.56%)	1291 (17.77%)	1160 (20.89%)	42 (17.21%)	271 (17.65%)	162 (14.59%)
	twice-month	531 (5.59%)	537 (7.39%)	527 (9.49%)	16 (6.56%)	98 (6.38%)	85 (7.66%)
	twice-week	560 (5.90%)	451 (6.21%)	484 (8.72%)	28 (11.48%)	78 (5.08%)	64 (5.77%)
Two-wheeled motorcycle	everyday	74 (0.78%)	107 (1.47%)	19 (0.34%)	7 (2.87%)	18 (1.17%)	10 (0.90%)
	never	9130 (96.14%)	6740 (92.79%)	5409 (97.42%)	219 (89.75%)	1431 (93.22%)	1037 (93.42%)
	rarely	147 (1.55%)	195 (2.68%)	53 (0.95%)	6 (2.46%)	35 (2.28%)	24 (2.16%)
	twice-month	61 (0.64%)	126 (1.73%)	24 (0.43%)	3 (1.23%)	22 (1.43%)	17 (1.53%)
	twice-week	77 (0.81%)	92 (1.27%)	36 (0.65%)	9 (3.69%)	27 (1.76%)	21 (1.89%)

Table A.5: Usage frequency of private transportation modes of the surveyed individuals of the urban area of Lyon per group in the typology.

Lyon: Frequency of walking and usage of the public transportation system.							
	Frequency	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Walking	everyday	5655 (59.55%)	3383 (46.57%)	3888 (70.03%)	143 (58.61%)	689 (44.89%)	620 (55.86%)
	never	634 (6.68%)	1026 (14.12%)	424 (7.64%)	19 (7.79%)	204 (13.29%)	102 (9.19%)
	rarely	846 (8.91%)	941 (12.95%)	402 (7.24%)	17 (6.97%)	208 (13.55%)	125 (11.26%)
	twice-month	475 (5.00%)	498 (6.86%)	191 (3.44%)	10 (4.10%)	93 (6.06%)	46 (4.14%)
	twice-week	1879 (19.79%)	1412 (19.44%)	636 (11.46%)	55 (22.54%)	339 (22.08%)	216 (19.46%)
Train	everyday	78 (0.82%)	324 (4.46%)	185 (3.33%)	8 (3.28%)	27 (1.76%)	15 (1.35%)
	never	6619 (69.70%)	5019 (69.09%)	3959 (71.31%)	136 (55.74%)	1129 (73.55%)	724 (65.23%)
	rarely	2230 (23.48%)	1547 (21.30%)	1073 (19.33%)	67 (27.46%)	320 (20.85%)	276 (24.86%)
	twice-month	441 (4.64%)	266 (3.66%)	221 (3.98%)	23 (9.43%)	47 (3.06%)	71 (6.40%)
	twice-week	121 (1.27%)	104 (1.43%)	103 (1.86%)	10 (4.10%)	10 (0.65%)	23 (2.07%)
Other PTS	everyday	1202 (12.66%)	1383 (19.04%)	2130 (38.36%)	81 (33.20%)	250 (16.29%)	162 (14.59%)
	never	3910 (41.17%)	3181 (43.79%)	1623 (29.23%)	68 (27.87%)	766 (49.90%)	428 (38.56%)
	rarely	1898 (19.99%)	1460 (20.10%)	857 (15.44%)	34 (13.93%)	306 (19.93%)	223 (20.09%)
	twice-month	1221 (12.86%)	708 (9.75%)	400 (7.20%)	26 (10.66%)	122 (7.95%)	149 (13.42%)
	twice-week	1258 (13.25%)	528 (7.27%)	531 (9.56%)	35 (14.34%)	89 (5.80%)	147 (13.24%)

Table A.6: Frequency of walking and usage of public transportation system (PTS) of the surveyed individuals of the urban area of Lyon per group in the typology of activity programs.

Rennes: Socio-demographic aspects of individuals.							
	Categories	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Age	05-17	82 (2.13%)	8 (0.27%)	1758 (85.71%)	2 (0.37%)	11 (5.82%)	17 (3.66%)
	18-24	130 (3.38%)	138 (4.58%)	277 (13.51%)	35 (6.49%)	24 (12.70%)	27 (5.82%)
	25-34	323 (8.41%)	605 (20.09%)	15 (0.73%)	96 (17.81%)	44 (23.28%)	39 (8.41%)
	35-49	541 (14.08%)	1321 (43.86%)	1 (0.05%)	236 (43.78%)	48 (25.40%)	74 (15.95%)
	50-64	1006 (26.19%)	927 (30.78%)	-	165 (30.61%)	47 (24.87%)	135 (29.09%)
	65+	1759 (45.80%)	13 (0.43%)	-	5 (0.93%)	15 (7.94%)	172 (37.07%)
Gender	female	2280 (59.36%)	1470 (48.80%)	1049 (51.15%)	278 (51.58%)	78 (41.27%)	244 (52.59%)
	male	1561 (40.64%)	1542 (51.20%)	1002 (48.85%)	261 (48.42%)	111 (58.73%)	220 (47.41%)
Working Status	full-time employment	655 (17.05%)	2585 (85.82%)	2 (0.10%)	418 (77.55%)	113 (59.79%)	100 (21.55%)
	internship	11 (0.29%)	42 (1.39%)	4 (0.20%)	5 (0.93%)	1 (0.53%)	2 (0.43%)
	other	46 (1.20%)	1 (0.03%)	-	-	-	5 (1.08%)
	part-time employment	252 (6.56%)	351 (11.65%)	-	108 (20.04%)	22 (11.64%)	29 (6.25%)
	retired	2209 (57.51%)	7 (0.23%)	-	5 (0.93%)	19 (10.05%)	238 (51.29%)
	school student	80 (2.08%)	2 (0.07%)	1814 (88.44%)	-	10 (5.29%)	17 (3.66%)
	stay at home	177 (4.61%)	2 (0.07%)	-	-	-	18 (3.88%)
	unemployed	358 (9.32%)	8 (0.27%)	-	-	10 (5.29%)	41 (8.84%)
	university student	53 (1.38%)	14 (0.46%)	231 (11.26%)	3 (0.56%)	14 (7.41%)	14 (3.02%)
Socio-professional Category	blue collar workers	593 (15.44%)	378 (12.55%)	1 (0.05%)	146 (27.09%)	48 (25.40%)	53 (11.42%)
	business owners and shopkeepers	204 (5.31%)	84 (2.79%)	-	16 (2.97%)	4 (2.12%)	23 (4.96%)
	employees	1245 (32.41%)	875 (29.05%)	1 (0.05%)	190 (35.25%)	54 (28.57%)	129 (27.80%)
	executive and professionals	559 (14.55%)	766 (25.43%)	-	46 (8.53%)	19 (10.05%)	70 (15.09%)
	farmers	152 (3.96%)	20 (0.66%)	-	4 (0.74%)	3 (1.59%)	10 (2.16%)
	no professional activity	248 (6.46%)	60 (1.99%)	2049 (99.90%)	8 (1.48%)	27 (14.29%)	46 (9.91%)
	technicians and associate professionals	840 (21.87%)	829 (27.52%)	-	129 (23.93%)	34 (17.99%)	133 (28.66%)

Table A.7: Socio-demographic aspects of surveyed individuals in the urban area of Rennes per group of the typology of activity programs.

Rennes: Usage frequency of different transportation modes.							
	Frequency	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Car/Van as driver	multi-days-month	375 (9.76%)	142 (4.71%)	58 (2.83%)	19 (3.53%)	18 (9.52%)	35 (7.54%)
	multi-days-week	2630 (68.47%)	2581 (85.69%)	145 (7.07%)	462 (85.71%)	137 (72.49%)	343 (73.92%)
	never	641 (16.69%)	163 (5.41%)	1820 (88.74%)	46 (8.53%)	24 (12.70%)	67 (14.44%)
	rarely	193 (5.02%)	125 (4.15%)	27 (1.32%)	12 (2.23%)	9 (4.76%)	18 (3.88%)
Bicycle	multi-days-month	284 (7.39%)	226 (7.50%)	253 (12.34%)	34 (6.31%)	16 (8.47%)	32 (6.90%)
	multi-days-week	406 (10.57%)	252 (8.37%)	214 (10.43%)	52 (9.65%)	24 (12.70%)	69 (14.87%)
	never	2244 (58.42%)	1653 (54.88%)	862 (42.03%)	291 (53.99%)	96 (50.79%)	226 (48.71%)
	rarely	905 (23.56%)	880 (29.22%)	721 (35.15%)	162 (30.06%)	52 (27.51%)	136 (29.31%)
PTS	multi-days-month	404 (10.52%)	210 (6.97%)	137 (6.68%)	36 (6.68%)	21 (11.11%)	52 (11.21%)
	multi-days-week	492 (12.81%)	347 (11.52%)	871 (42.47%)	63 (11.69%)	36 (19.05%)	76 (16.38%)
	never	1662 (43.27%)	1432 (47.54%)	663 (32.33%)	268 (49.72%)	72 (38.10%)	192 (41.38%)
	rarely	1281 (33.35%)	1022 (33.93%)	379 (18.48%)	172 (31.91%)	59 (31.22%)	143 (30.82%)
TER	multi-days-month	65 (1.69%)	33 (1.10%)	29 (1.41%)	9 (1.67%)	2 (1.06%)	9 (1.94%)
	multi-days-week	27 (0.70%)	94 (3.12%)	27 (1.32%)	6 (1.11%)	2 (1.06%)	5 (1.08%)
	never	2938 (76.49%)	2401 (79.71%)	1670 (81.42%)	423 (78.48%)	145 (76.72%)	344 (74.14%)
	rarely	809 (21.06%)	483 (16.04%)	324 (15.80%)	101 (18.74%)	39 (20.63%)	105 (22.63%)
Two-wheeled	multi-days-month	40 (1.04%)	48 (1.59%)	4 (0.20%)	8 (1.48%)	5 (2.65%)	6 (1.29%)
	multi-days-week	47 (1.22%)	66 (2.19%)	15 (0.73%)	17 (3.15%)	7 (3.70%)	6 (1.29%)
	never	3674 (95.65%)	2766 (91.83%)	2018 (98.39%)	493 (91.47%)	168 (88.89%)	430 (92.67%)
	rarely	78 (2.03%)	131 (4.35%)	13 (0.63%)	21 (3.90%)	8 (4.23%)	21 (4.53%)
Walking	multi-days-month	346 (9.01%)	401 (13.31%)	234 (11.41%)	69 (12.80%)	15 (7.94%)	46 (9.91%)
	multi-days-week	2753 (71.67%)	1554 (51.59%)	1377 (67.14%)	296 (54.92%)	117 (61.90%)	321 (69.18%)
	never	221 (5.75%)	399 (13.25%)	141 (6.87%)	56 (10.39%)	17 (8.99%)	34 (7.33%)
	rarely	519 (13.51%)	657 (21.81%)	298 (14.53%)	118 (21.89%)	39 (20.63%)	62 (13.36%)

Table A.8: Usage frequency of different transportation modes of the surveyed individuals of the urban area of Rennes per group in the typology of activity programs.

Territorial Partitions of Studied Regions

Rennes, France

Small Areas (570 locations)

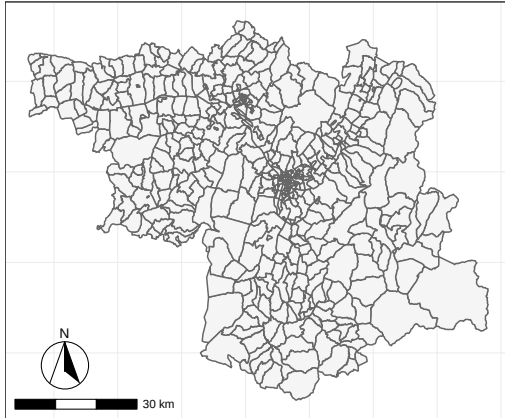


Polling Districts (68 locations)



Grenoble, France

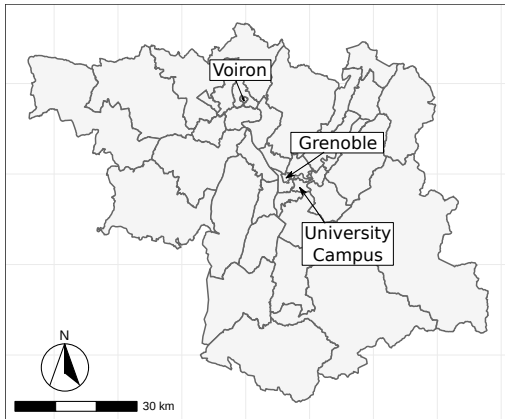
Small Areas (526 locations)



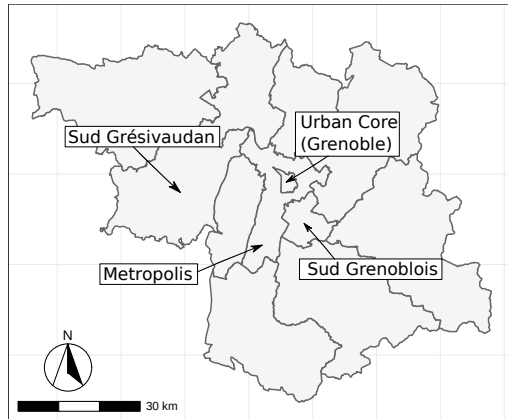
Polling Districts (97 locations)



Intermediate Areas (39 locations)

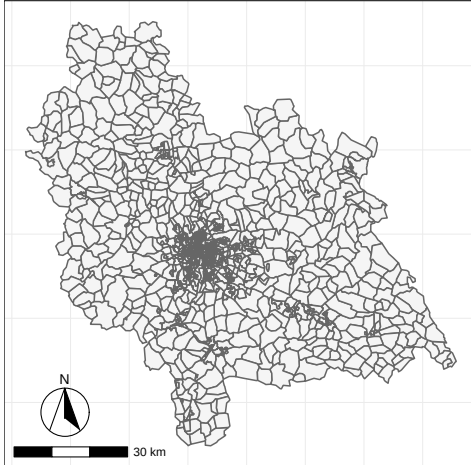


Large Areas (12 locations)

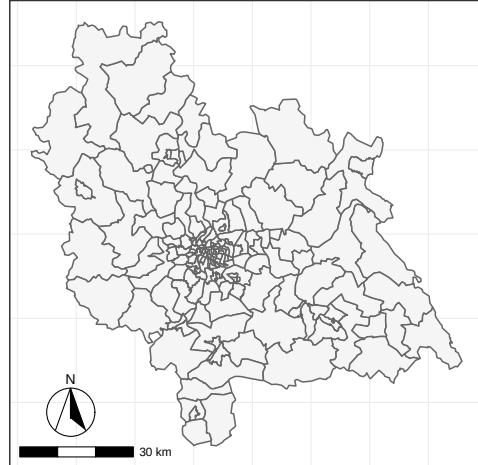


Lyon, France

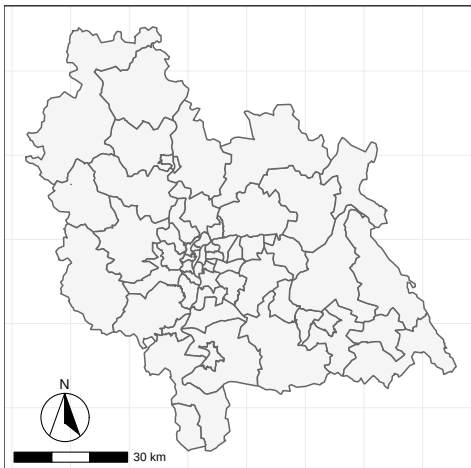
Small Areas (1191 locations)



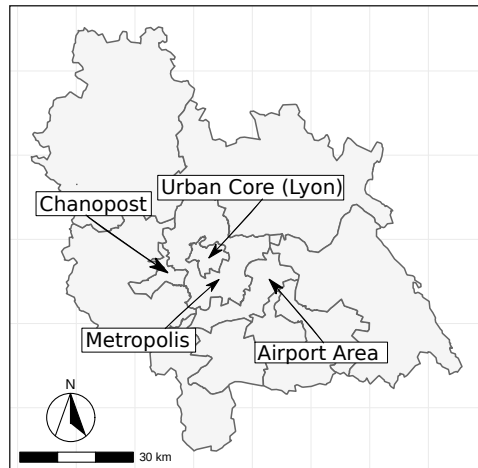
Polling Districts (169 locations)



Intermediate Areas (58 locations)



Large Areas (12 locations)



Mutual Materials and Methods of Experiments

C.1 NASA TLX Questionnaire

The evaluation you are about to perform is a technique that has been developed by NASA to assess the relative importance of six factors in determining how much workload you experienced:

- **MENTAL DEMAND** – How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching)? Was the task easy or demanding, simple or complex, exacting or forgiving?
- **PHYSICAL DEMAND** – How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
- **TEMPORAL DEMAND** – How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
- **EFFORT** – How hard did you have to work (mentally and physically) to accomplish your level of performance?
- **PERFORMANCE** – How successful do you think you were in accomplishing the goals of the task set by the experimenter? How satisfied were you with your performance in accomplishing these goals?
- **FRUSTRATION LEVEL** – How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

NASA TLX Questionnaire Part 1 (Sources of Load)		
1	(A) Mental Demand or Effort (B)	<input type="checkbox"/> A <input type="checkbox"/> B
2	(A) Frustration or Effort (B)	<input type="checkbox"/> A <input type="checkbox"/> B
3	(A) Temporal Demand or Mental Demand (B)	<input type="checkbox"/> A <input type="checkbox"/> B
4	(A) Performance or Frustration (B)	<input type="checkbox"/> A <input type="checkbox"/> B
5	(A) Effort or Physical Demand (B)	<input type="checkbox"/> A <input type="checkbox"/> B
6	(A) Temporal Demand or Effort (B)	<input type="checkbox"/> A <input type="checkbox"/> B
7	(A) Physical Demand or Temporal Demand (B)	<input type="checkbox"/> A <input type="checkbox"/> B
8	(A) Performance or Temporal Demand (B)	<input type="checkbox"/> A <input type="checkbox"/> B
9	(A) Effort or Performance (B)	<input type="checkbox"/> A <input type="checkbox"/> B
10	(A) Performance or Mental Demand (B)	<input type="checkbox"/> A <input type="checkbox"/> B
11	(A) Physical Demand or Frustration (B)	<input type="checkbox"/> A <input type="checkbox"/> B
12	(A) Frustration or Mental Demand (B)	<input type="checkbox"/> A <input type="checkbox"/> B
13	(A) Temporal Demand or Frustration(B)	<input type="checkbox"/> A <input type="checkbox"/> B
14	(A) Physical Demand or Performance (B)	<input type="checkbox"/> A <input type="checkbox"/> B
15	(A) Mental Demand or Physical Demand (B)	<input type="checkbox"/> A <input type="checkbox"/> B
NASA TLX Questionnaire Part 2 (Magnitude of Load)		
1	How mentally demanding was the task?	Low High 1 2 3 4 5 6 7 8 9 10 <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
2	How physically demanding was the task?	Low High 1 2 3 4 5 6 7 8 9 10 <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
3	How hurried or rushed was the pace of the task?	Low High 1 2 3 4 5 6 7 8 9 10 <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
4	How successful were you in accomplishing what you were asked to do?	Low High 1 2 3 4 5 6 7 8 9 10 <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
5	How hard did you have to work to accomplish your level of performance?	Low High 1 2 3 4 5 6 7 8 9 10 <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
6	How insecure, discouraged, irritated, stressed, and annoyed were you?	Low High 1 2 3 4 5 6 7 8 9 10 <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

Source: Hart and Staveland (1988).

C.2 Raw NASA TLX Questionnaire

Raw TLX Questionnaire ⁱ	
<p>Cette évaluation prend en compte six dimensions indépendants (expliqués ci-dessous) que vous devez évaluer en fonction de votre ressenti.</p> <p>EXIGENCE MENTALE : Quelle a été l'importance de l'activité mentale et intellectuelle requise (ex. réflexion, décision, calcul, mémorisation, observation, recherche, etc) ? La tâche vous a-t-elle paru simple, nécessitant peu d'attention (faible) ou complexe, nécessitant beaucoup d'attention (élevée) ?</p> <p>EXIGENCE PHYSIQUE : Quelle a été l'importance de l'activité physique requise (ex. pousser, porter, tourner, marcher, activer, etc) ? La tâche vous a-t-elle paru facile, peu fatigante, calme (faible) ou pénible, fatigante, active (élevée) ?</p> <p>EXIGENCE TEMPORELLE : Quelle a été l'importance de la pression temporelle causée par la rapidité nécessitée pour l'accomplissement de la tâche ? Etait-ce un rythme lent et tranquille (faible) ou rapide et précipité (élevé) ?</p> <p>PERFORMANCE : Quel niveau de réussite pensez-vous avoir eu dans l'accomplissement de votre tâche ? Comment pensez-vous avoir atteint les objectifs déterminés par la tâche ?</p> <p>EFFORT : Quel degré d'effort avez-vous dû fournir pour exécuter la tâche demandée (mentalement et physiquement) ?</p> <p>FRUSTRATION : Pendant l'exécution du travail êtes-vous senti satisfait, relaxé, sûr de vous (niveau de frustration faible), ou plutôt découragé, irrité, stressé, sans assurance (niveau de frustration élevé) ?</p>	
1	<p>Quel degré d'activité mentale était exigé pour réaliser la tâche ?</p> <p>Low High</p> <p>1 2 3 4 5 6 7 8 9 10</p> <p><input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/></p>
2	<p>Quel degré d'activité physique était exigé pour réaliser la tâche ?</p> <p>Low High</p> <p>1 2 3 4 5 6 7 8 9 10</p> <p><input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/></p>
3	<p>Quelle pression temporelle avez-vous ressentie pour réaliser la tâche ?</p> <p>Low High</p> <p>1 2 3 4 5 6 7 8 9 10</p> <p><input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/></p>
4	<p>Avec quel succès pensez-vous avoir réalisé la tâche ?</p> <p>Low High</p> <p>1 2 3 4 5 6 7 8 9 10</p> <p><input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/></p>
5	<p>Quel effort deviez-vous fournir pour accomplir la tâche ?</p> <p>Low High</p> <p>1 2 3 4 5 6 7 8 9 10</p> <p><input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/></p>
6	<p>Avez-vous ressenti, durant votre tâche, de l'insecurité, du découragement, de l'irritation, du stress ou de l'agacement ?</p> <p>Low High</p> <p>1 2 3 4 5 6 7 8 9 10</p> <p><input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/></p>

ⁱ French translation recovered from https://theses.univ-lyon2.fr/documents/getpart.php?id=lyon2.2010.mai_ncent_a&part=365749

C.3 SUS Questionnaire

SUS Questionnaire						
Please rate the following statements from 1 to 5 according to how much you agree with it						
1	I think that I would like to use this system frequently	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
2	I found the system unnecessarily complex	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
3	I thought the system was easy to use	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
4	I think I would need the support of a technical person to be able to use this system	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
5	I found the various functions in this system were well integrated	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
6	I thought there was too much inconsistency in this system	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
7	I would imagine that most people would learn to use this system very quickly	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
8	I found the system very cumbersome to use	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
9	I felt very confident using the system	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>
10	I needed to learn a lot of things before I could get going with this system	Strongly Disagree 1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	Strongly Agree 4 <input type="checkbox"/>	5 <input type="checkbox"/>

Source: Brooke (1996).

Le Questionnaire SUS ⁱ						
Pour chaque affirmation ci-dessous, merci de cocher la case qui correspond le mieux à votre niveau d'appréciation.						
1	Je pense que j'aimerais utiliser fréquemment ce système	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2	J'ai trouvé ce système inutilement complexe	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
3	J'ai trouvé ce système facile à utiliser.	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
4	Je pense que j'aurais besoin du support d'un spécialiste pour utiliser ce système	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
5	J'ai trouvé que les différentes fonctions de ce système étaient bien intégrées	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
6	J'ai trouvé ce système trop incohérent	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
7	Je pense que ce système sera facile à apprendre pour beaucoup de personnes	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
8	J'ai trouvé ce système très contraignant à utiliser	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
9	Je me suis senti(e) en confiance lorsque j'ai utilisé ce système	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
10	J'ai dû apprendre beaucoup de choses avant de me sentir familiarisé(e) avec ce système	Pas du tout d'accord			Tout à fait d'accord	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

ⁱ French translation recovered from https://fr.ryte.com/wiki/System_Usability_Scale#Le_questionnaire

Experiment I: Questionnaires and Tasks

D.1 Tasks Description

Preliminary information:

- The tasks focus on the following time intervals: morning (between 7am and 8am), noon (from 12pm to 1pm), and evening (from 6pm to 7pm).
- The movement required for animating time through the TM technique depends on the experiment condition, which is counterbalanced with the tasks sets. It may be a rotational movement in a clock- and counterclockwise manner or from left to right and contrariwise. The users learned the required movement just before solving the tasks.
- EXPLORE and NEXT are control buttons of the slide-like presentation of tasks on the Control Unit interface. The former allows to begin the exploration of indicators to complete the task at hand, while the latter allows to record the time elapsed since the user clicked on EXPLORE, i.e. the task's completion time.
- At the time of this experiment, the analytical dashboards were called *Visualization Spaces*.

The tasks of **Set 1**:

- Task 1.** Give the **presence density** of location 5 during the morning period. Click on EXPLORE to start the task. Then follow the instructions below:

- Open the presence density indicator by using the main menu.
- Explore the indicator's variation over time by tilting the tablet as you did on the training phase
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on the Control Unit interface.

Reply:

Task 2. Give the mobility rate for the whole region during the morning and evening periods.

Click on EXPLORE to start the task. Then follow the instructions below:

- Open the mobility rate indicator by using the main menu.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on a Visualization Space.

Reply:

Task 3. Give the transportation modes share for the whole region during the morning, noon and evening periods.

Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following indicators:
 - Mobility rate by using the main menu.
 - Histograms for the transportation modes share of every required time periods.
- Use it to complete the task.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on a Visualization Space.

Reply:

Task 4. Identify where the majors incoming travel flows to the three **most attractive** locations over 24 hours come from. Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following indicators using the main menu:
 - Attractiveness.
 - Flows.
- Use it to complete the task.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on a Visualization Space.

Reply:

Task 5. Classify locations 1, 6, 61 and 51 according to the transportation modes share during the morning, noon and evening periods. Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following:
 - Mobility rate indicator for every required location. Reminder: use the menu available in each location on the map.
 - Histograms with the transportation modes share of every required time periods.
- Use it to complete the task.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on a Visualization Space.

Reply:

Task 6. For each time period (i.e. morning, noon, evening), choose a location that presents a **positive** fluctuation rate. Then, for each chosen location, give the transportation modes share during the morning, noon, and evening periods. Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following indicators:
 - Fluctuation rate. Reminder: use the main menu.
 - Mobility rate for every chosen location. Reminder: use the menu available in each location.
 - Histograms for the transportation modes share of every required time period.

- Explore the variation of fluctuation rate indicator over time by tilting the tablet.
- Use it to complete the task.
- Write your answer below. List the chosen locations in your answer.
- Open the task description on the tablet, and click on NEXT.

Obs.: Display the fluctuation rate on the Control Unit interface and the remaining indicators in a Visualization Space.

Reply:

The tasks of **Set 2**:

Task 1. Give the **fluctuation rate** of location 6 during the morning period. Click on EXPLORE to start the task. Then follow the instructions below:

- Open the fluctuation rate indicator by using the main menu.
- Explore this indicator's variation over time by tilting the tablet.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on the Control Unit interface.

Reply:

Task 2. List the five most attractive locations in descending order of attractiveness.

Click on EXPLORE to start the task. Then follow the instructions below:

- Open the attractiveness indicator by using the main menu.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on the Control Unit interface.

Reply:

Task 3. Identify the time period when the two most attractive locations have the highest mobility rate.

Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following indicators using the main menu:
 - Attractiveness.
 - Fluctuation rate.
- Explore the fluctuation rate indicator's variation over time by tilting the tablet.
- Use it to complete the task.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: Display the fluctuation rate on the Control Unit interface and the remaining indicators in a Visualization Space.

Reply:

Task 4. Identify where the major outgoing travel flows from the two **less attractive** locations over 24 hours are going to.

Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following indicators using the main menu:
 - Attractiveness.
 - Flows.
- Use it to complete the task.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on a Visualization Space.

Reply:

Task 5. Identify the two locations with the higher overall mobility rate among locations 2, 6, 61, and 51.

Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following indicators using the menu available on each location:

- Mobility rate for every required location.
- Use it to complete the task.
- Write your answer below.
- Open the task description on the tablet, and click on NEXT.

Obs.: You must display this representation on a Visualization Space.

Reply:

Task 6. For each time period (i.e. morning, noon, evening), choose a location that presents a **negative** fluctuation rate. Then, for each chosen location, give the transportation modes share during the morning, noon, and evening periods. Click on EXPLORE to start the task. Then follow the instructions below:

- Display the following indicators:
 - Fluctuation rate. Reminder: use the main menu.
 - Mobility rate for every chosen location. Reminder: use the menu available in each location.
 - Histograms for the transportation modes share of every required time period.
- Explore the variation of fluctuation rate indicator over time by tilting the tablet.
- Use it to complete the task.
- Write your answer below. List the chosen locations in your answer.
- Open the task description on the tablet, and click on NEXT.

Obs.: Display the fluctuation rate on the Control Unit interface and the remaining indicators in a Visualization Space.

Reply:

D.2 Terms and Conditions Agreement

You are invited to take part in an experiment to evaluate the usability and effectiveness of a visualization interface for exploring daily mobility data. The present document aims to explain the experiment objective, procedures, risks, and protocol. Please read carefully this document and clarify your doubts before consenting your participation in this study.

Procedure: the participant will be required to complete two sets of tasks using the visualization interface and two interaction styles for exploring data over time. The whole process will last around one hour (1:00) and consists of five (5) steps, as follows:

1. Socio-demographic questionnaire.
2. Learning how to use the visual and interaction tools under evaluation.
3. For each experimental condition (there are 2), the participant will complete a set of six (6) tasks regarding the population mobility patterns within the region of Grenoble metropolitan area, and answer a questionnaire to assess their perceived workload.
4. Post-test questionnaire, in which the participant will be requested to answer questions that subjectively evaluate the usability, perceived task workload and preference over the two experimental conditions, and to voluntarily give their opinion regarding the visual and interaction tools, and the experiment itself.

Risks: the present study does not represent any risks for the participant.

Benefits: the participant could contribute for the refinement of a visualization tool designed to assist the analysis of urban mobility data, which outcomes are used for decision-making on transportation offers, urban planning, and so on.

All the data collected in this experiment will be only used in this study and in a completely anonymous way.

The participant is free to abandon the test, without any prejudice, if they wish to do so.

Please check the field below if you agree with the termsⁱ

I agree to participate in this experiment. I have been properly informed about the procedures, risks, and benefits of this study, and the confidentiality of my information and the removal of my consent at any moment have been granted.

ⁱ The agreement was applied via an online form. No signature was required.

D.3 Socio-demographic Questionnaire

User ID						
Socio-demographic Profile						
1	Age					
2	Gender	<input type="checkbox"/> Female <input type="checkbox"/> Male				
3	Primary Language					
4	Profession					
5	Do you have any medical condition involving your wrists?	<input type="checkbox"/> Yes <input type="checkbox"/> No <input type="checkbox"/> I don't know				
6	If you marked "yes" in the previous question, please specify the issue.					
7	Do you live in the Rhône-Alpes Region?	<input type="checkbox"/> Yes <input type="checkbox"/> No				
8	If you said "yes", how long do you live there?					
Experience						
9	How do you classify your knowledge about human mobility patterns within the Rhône-Alpes region?	Beginner			Advanced	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
10	How do you classify your experience on GIS?	Beginner			Advanced	
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Experiment II: Questionnaires

E.1 UMUX-Lite Questionnaire

User ID						
Experimental Condition		<input type="checkbox"/> TM Circular <input type="checkbox"/> TM Linear <input type="checkbox"/> TA Mouse <input type="checkbox"/> TA Linear				
Please rate the following statements from 1 to 5 according to how much you agree with it						
1	Using this interaction interface is a frustrating experience	Strongly Disagree		Strongly Agree		
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2	This interface is easy to use	Strongly Disagree		Strongly Agree		
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

The questionnaire was adapted from [Lewis et al. \(2013\)](#)

E.2 Preference Questionnaire

User ID							
Please rate the following statements from 1 to 5 according to how much you agree with it							
1	I enjoyed tilting the tablet for controlling the clock.	Strongly Disagree			Strongly Agree		
		1	2	3	4	5	
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
2	I enjoyed tilting the tablet for controlling the timeline.	Strongly Disagree			Strongly Agree		
		1	2	3	4	5	
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
3	I enjoyed controlling the animation by touching the screen.	Strongly Disagree			Strongly Agree		
		1	2	3	4	5	
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
4	I enjoyed controlling the animation by using the mouse cursor.	Strongly Disagree			Strongly Agree		
		1	2	3	4	5	
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
For each pair, please choose the interaction technique you enjoyed better							
1	(A) TM Circular or (B) TM Linear	<input type="checkbox"/>	A			<input type="checkbox"/>	B
2	(A) TA Touch or (B) TM Circular	<input type="checkbox"/>	A			<input type="checkbox"/>	B
3	(A) TM Circular or (B) TA Mouse	<input type="checkbox"/>	A			<input type="checkbox"/>	B
4	(A) TM Linear or (B) TA Touch	<input type="checkbox"/>	A			<input type="checkbox"/>	B
5	(A) TA Mouse or (B) TA Touch	<input type="checkbox"/>	A			<input type="checkbox"/>	B
6	(A) TA Mouse or (B) TM Linear	<input type="checkbox"/>	A			<input type="checkbox"/>	B

Source: the author.

E.3 Terms and Conditions Agreement

You are invited to take part in an experiment to evaluate the usability and effectiveness of a movement-based cartographic interface for exploring the temporal dynamics of urban mobility data. Please read carefully this document and clarify your questions before consenting your participation in this study.

Procedure: the participant will be required to answer simple questions regarding the population mobility patterns within the region of Grenoble metropolitan area via the exploration of presence density and fluctuation maps, and using the following interaction techniques:

1. *TM Circular*, which requires the participant to perform a rotational tilting movement of a tablet in order to select time periods on a virtual circular time picker.
2. *TM Linear*, which requires the participant to perform a tilting movement with a tablet from left to right and vice versa in order to select time periods on a virtual linear time picker.
3. *TA Touch*, which changes the time periods automatically and the participant can control (start, stop, resume) by direct touching the buttons on tablet screen.
4. *TA Mouse*, which changes the time periods automatically and the participant can control (start, stop, resume) by using the mouse to click on the buttons displayed on the computer screen.

The experiment take up to 30 minutes and consists of four (4) steps, as follows:

1. Socio-demographic questionnaire.
2. Learning how to use the interaction techniques under evaluation. A time of about 10 minutes (which can be variable) will be given to the participant for handling the interactive interface.
3. For each interaction technique, the participant will complete a set of three (3) simple tasks regarding the variation of presence **density** or **fluctuation** over time within the region of Grenoble metropolitan area, and answer a short usability questionnaire.
4. Post-test questionnaire, in which the participant is requested to answer questions that subjectively evaluate perceived task workload and preference regarding the tried interaction techniques, and to voluntarily give their opinion regarding the visual and interaction tools, and the experiment itself.

Risks: the present study does not represent any risks for the participant.

Benefits: the participant could contribute for improving the development of a interaction technique for exploring data over time.

All the data collected in this experiment will be only used in this study and in a completely anonymous way.

The participant is free to abandon the test, without any prejudice, if they wish to do so.

Please check the field below if you agree with the termsⁱ

I agree to participate in this experiment. I have been properly informed about the procedures, risks, and benefits of this study, and the confidentiality of my information and the removal of my consent at any moment have been granted.

ⁱ The agreement was applied via an online form. No signature was required.

E.4 Socio-demographic Questionnaire

User ID						
Socio-demographic Profile						
1	Age					
2	Gender	<input type="checkbox"/> Female <input type="checkbox"/> Male <input type="checkbox"/> Prefer not to say				
3	Profession					
4	Are you color-blind?	<input type="checkbox"/> Yes <input type="checkbox"/> No				
5	Are you right- or left-handed?	<input type="checkbox"/> Right-handed <input type="checkbox"/> Left-handed				
6	Do you have any medical condition on your wrists?	<input type="checkbox"/> Yes <input type="checkbox"/> No <input type="checkbox"/> I don't know				
7	If you marked "yes" in the previous question, please specify the issue.					
Experience						
8	How do you classify your knowledge about human mobility patterns within the region of Grenoble metropolitan area?	Beginner		Advanced		
		1	2	3	4	5
		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
9	How often do you use non-conventional devices (e.g., mobile devices, gesture sensors, game controllers) for interacting with your computer?	<input type="checkbox"/> Never <input type="checkbox"/> Rarely (once or twice a year) <input type="checkbox"/> Occasionally (5 or 6 times a year) <input type="checkbox"/> Often (once a month) <input type="checkbox"/> Always				
10	If you answered "Often" or "Always" on the previous question, please specify which interaction devices you use.					

Experiment III: Questionnaires and Tasks

F.1 Tasks Description (Learning Phase)

Preliminary information¹:

- The tasks should be answered using the *territorial partition* into intermediate areas of the great region of Grenoble metropolitan area (selected by default).
- The *time intervals* of interest are: morning (from 7am to 10am), noon (from 10am to 14pm), and evening (from 5pm to 8pm).
- The *spatial locations* of interest are 1 (Grenoble city center), 2 (Grenoble without city center), from 3 to 10 (remaining locations of Grenoble metropolitan area), 40 (Sud Grenoblois), from 50 to 53 (Voironnais). Use these spatial locations to complete tasks that do not specify a location.

Set 1. Spatial distribution of people along the day

Task 1. Identify the spatial locations where people are predominantly present during the morning, noon and evening periods.

Task 2. Identify the most attractive spatial locations over 24 hours.

Task 3. Identify the time intervals when people visit the attractive locations.

¹The tasks were originally prepared and applied in French

Task 4. Identify the time intervals when the attractive locations are visited by a number of people smaller than their population size.

Task 5. Identify the spatial locations that have less people present than their population size in the morning, noon and evening periods.

Set 2. Variation of travel flows and trips along the day.

Task 1. Describe the variation of mobility rate in the whole region along the day.

Task 2. Identify the three most important incoming flows of locations 1, 5, 40, and 50 over 24 hours.

Task 3. Identify the transportation modes share of locations 1, 5, 40, and 50 during the morning, noon, and evening periods.

Task 4. Describe whether and how these locations are similar regarding their share of transportation modes.

Set 3. Combined analysis of variation of spatial distribution of people, travel flows, and trips along the day.

Task 1. Identify where the main incoming flows of the most attractive locations are coming from during the morning, noon, and evening periods.

Task 2. Identify where the main incoming flows of the two or three spatial locations which number of people visiting is **higher** than the population size are coming from and their transportation modes share during the morning, noon, and evening periods.

Task 3. Identify where the main outgoing flows from the two or three spatial locations which number of people visiting is **lower** than the population size are directed to and their transportation modes share during the morning, noon, and evening periods.

F.2 Terms and Conditions Agreement

Vous êtes invités à participer à une expérience visant à évaluer l'utilisabilité et l'efficacité d'une interface mobile multi-fenêtres interactive pour explorer les dynamiques spatio-temporelles à partir de l'analyse visuelle de données de mobilités urbaines. Veuillez lire attentivement les termes de l'expérimentation présentés ci-après et posez des questions si besoin (aux expérimentateurs/enseignants) avant de consentir à participer à cette étude.

Procédure: le participant doit répondre à des questions simples sur les mobilités urbaines caractérisant la région grenobloise au moyen de la visualisation de cartes et d'indicateurs graphiques en interrogeant les données selon des critères temporels et spatiaux. L'expérience dure environ 45 minutes et se décline en quatre étapes :

1. Un questionnaire socio-démographique.
2. Une formation préalable sur les modalités d'utilisation de l'interface. Cette formation sera réalisée en suivant une liste de tâches disponible sur l'application qui permettra au participant d'apprendre à manipuler l'interface.
3. L'expérimentation en tant que telle, contenant 14 questions sur la mobilité grenobloise auxquelles le participant doit répondre à l'aide des visualisations disponibles sur l'outil. Ce sont des indicateurs de densité de présence, de taux de migration et d'attractivité présenté au moyens de cartes choroplèthes ; ce sont aussi des indicateurs décrivant les déplacements des individus, représentés par une "roue de déplacements" et des diagrammes de flux.
4. Un questionnaire de retour d'expérience, qui vise à évaluer la charge de travail demandée par l'expérience et l'utilisabilité de l'outil pour l'analyse géovisuelle de la mobilité urbaine. De plus, le participant est invité à donner librement des commentaires sur son expérience et/ou sur l'interface.

Risques: la présente étude ne représente aucun risque pour le participant.

Toutes les données recueillies lors de cette expérience seront utilisées uniquement dans le cadre de cette étude et de manière totalement anonyme.

Cochez les cases suivantes si vous acceptez les termes suivants (ne pas cocher vaut pour désaccord) :

- J'autorise l'utilisation de mes données dans le cadre de cette recherche.
- J'autorise l'utilisation des images, prise pendant l'expérimentation, dans le cadre de cette recherche.

Le participant est libre d'abandonner le test, sans aucun préjudice, s'il le souhaite.

Cochez la case suivante si vous acceptez de participer à cette recherche :

- J'accepte de participer à cette expérimentation. J'ai été correctement informé des procédures, des risques et des avantages de cette étude. De plus, la confidentialité de mes informations et le retrait de mon consentement me sont accordés à tout moment.

Fait à Grenoble, le 19/12/2018.

Nom

Prénom

Identifiant

Signature du participant

F.3 Socio-Demographic Questionnaire

Identifiant du participant																								
Profil socio-demographique																								
1	Âge																							
2	Sexe	<input type="checkbox"/> Féminin <input type="checkbox"/> Masculin <input type="checkbox"/> Je ne souhaite pas le préciser																						
3	Êtes-vous daltonien ?	<input type="checkbox"/> Yes <input type="checkbox"/> No																						
4	Portez-vous des lunettes ?	<input type="checkbox"/> Yes <input type="checkbox"/> No																						
5	Avez-vous ou avez-vous déjà eu des douleurs aux poignets ?	<input type="checkbox"/> Yes <input type="checkbox"/> No																						
Experience																								
6	Quel est votre niveau de connaissance sur la thématique des mobilités quotidiennes dans la région grenobloise ?	<table style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th colspan="2" style="text-align: left;">Débutant</th> <th colspan="3"></th> <th style="text-align: right;">Expert</th> </tr> <tr> <th style="width: 15%;">1</th> <th style="width: 15%;">2</th> <th style="width: 15%;">3</th> <th style="width: 15%;">4</th> <th style="width: 15%;">5</th> <th></th> </tr> </thead> <tbody> <tr> <td style="text-align: center;"><input type="checkbox"/></td> <td style="text-align: center;"><input type="checkbox"/></td> <td style="text-align: center;"><input type="checkbox"/></td> <td style="text-align: center;"><input type="checkbox"/></td> <td style="text-align: center;"><input type="checkbox"/></td> <td style="text-align: center;"><input type="checkbox"/></td> </tr> </tbody> </table>					Débutant					Expert	1	2	3	4	5		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Débutant					Expert																			
1	2	3	4	5																				
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>																			
7	A quelle fréquence utilisez-vous des dispositifs autre que la souris et le clavier pour interagir avec votre ordinateur ?	<input type="checkbox"/> Jamais <input type="checkbox"/> Rarement (une ou deux fois par an) <input type="checkbox"/> Parfois (5 ou 6 fois par an) <input type="checkbox"/> Souvent (au moins une fois par mois) <input type="checkbox"/> Toujours																						
8	Si vous avez répondu 'souvent' ou 'toujours' à la question précédente, merci de préciser le type de dispositif utilisé.																							

APPENDIX G

Experiment IV: Questionnaires

G.1 Terms and Conditions Agreement

Vous êtes invités à participer à une expérience visant à évaluer l'utilisabilité et l'efficacité d'une interface multi-fenêtres interactive pour explorer les dynamiques spatio-temporelles à partir d'une analyse visuelle de données de mobilités urbaines. Veuillez lire attentivement les termes de l'expérimentation présentés ci-après et posez des questions si besoin (aux expérimentateurs/enseignants) avant de consentir à participer à cette étude.

Procédure : Le participant doit s'approprier des indicateurs de mobilité disponibles sur l'application pour répondre à des questions sur trois points de vues complémentaires décrivant les patterns de mobilité urbaine : les flux et déplacements, la dynamique de peuplement du territoire et l'emploi du temps des individus. Cette analyse est basée sur la visualisation de cartes et de graphiques interconnectés entre eux et représentant des indicateurs de mobilité, interrogeables selon des critères temporels et spatiaux. L'expérience dure 3 heures et se déroule en quatre étapes :

1. Une présentation sur l'outil, les indicateurs de mobilité et les représentations disponibles.
2. Un questionnaire socio-démographique.
3. L'exploration de l'outil par le participant pour répondre aux trois questions ouvertes sur la mobilité de la population de Grenoble, Lyon ou Rennes.
4. Un questionnaire de retour d'expérience, qui vise à évaluer la charge de travail demandée par la réalisation de l'analyse et l'utilisabilité de l'outil pour l'analyse géovisuelle de la mobilité urbaine. De plus, le participant est invité à donner librement des commentaires sur son expérience et/ou sur l'interface.

Risques: la présente étude ne représente aucun risque pour le participant.

Toutes les données recueillies lors de cette expérience seront utilisées uniquement dans le cadre de cette étude et de manière totalement anonyme.

Le participant est libre d'abandonner le test, sans aucun préjudice, s'il le souhaite.

Cochez les cases suivantes si vous acceptez les termes suivants (ne pas cocher vaut pour désaccord)

:

J'autorise l'utilisation de mes données dans le cadre de cette recherche.

J'autorise l'utilisation des images, prise pendant l'expérimentation, dans le cadre de cette recherche.

Cochez la case suivante si vous acceptez de participer à cette recherche :

J'accepte de participer à cette expérimentation. J'ai été correctement informé des procédures, des risques et des avantages de cette étude. De plus, la confidentialité de mes informations et le retrait de mon consentement me sont accordés à tout moment.

Fait à Grenoble, le __/01/2020.

Nom

Prénom

Identifiant

Signature du participant